

Introduction to SCIP



ZIB: Fast Algorithms – Fast Computers

Konrad-Zuse-Zentrum für Informationstechnik Berlin



- ▷ non-university research institute of the state of Berlin
- ▷ Research Units:
 - ▶ numerical analysis and modeling
 - ▶ visualization and data analysis
 - ▶ **optimization**
 - ▶ scientific information systems
 - ▶ distributed algorithms and supercomputing
- ▷ more information: <http://www.zib.de>

09:00 – 10:30	Introduction and Overview
10:30 – 11:00	Coffee Break
11:00 – 12:30	Installation and Testing Environment
12:30 – 14:00	Lunch Break
14:00 – 15:00	Parameter Tuning
15:00 – 15:30	Coffee Break
15:30 – 17:30	Programming Exercise

WiFi:

- ▷ eduroam
- ▷ “Gast im ZIB” (no password)

SCIP – Solving Constraint Integer Programs

- 1 Constraint Integer Programming
- 2 Solving Constraint Integer Programs
- 3 The Solving Process of SCIP

<http://scip.zib.de>

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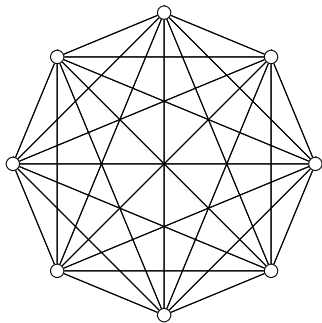
<http://scip.zib.de>

An example: the Traveling Salesman Problem

Definition (TSP)

Given a complete graph $G = (V, E)$ and distances d_e for all $e \in E$:

Find a **Hamiltonian cycle** (cycle containing all nodes, tour) of minimum length.



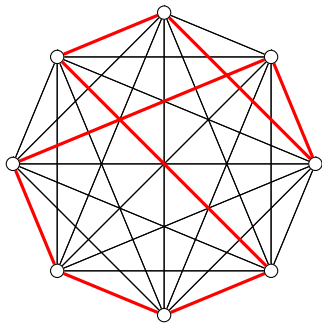
K_8

An example: the Traveling Salesman Problem

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What is a Constraint Integer Program?

Mixed Integer Program

Objective function:

- ▷ **linear** function

Feasible set:

- ▷ described by **linear** constraints

Variable domains:

- ▷ **real or integer** values

$$\begin{array}{ll}\min & c^T x \\ \text{s.t.} & Ax \leq b \\ & (x_I, x_C) \in \mathbb{Z}^I \times \mathbb{R}^C\end{array}$$

Constraint Program

Objective function:

- ▷ **arbitrary** function

Feasible set:

- ▷ given by **arbitrary** constraints

Variable domains:

- ▷ **arbitrary** (usually finite)

$$\begin{array}{ll}\min & c(x) \\ \text{s.t.} & x \in F \\ & (x_I, x_N) \in \mathbb{Z}^I \times X\end{array}$$

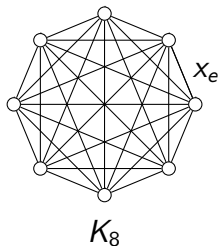
TSP – Integer Programming Formulation

Given

- ▷ complete graph $G = (V, E)$
- ▷ distances $d_e > 0$ for all $e \in E$

Binary variables

- ▷ $x_e = 1$ if edge e is used



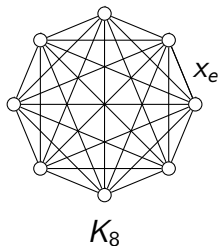
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$$\begin{array}{ll} \min & \sum_{e \in E} d_e x_e \\ \text{subject to} & \sum_{e \in \delta(v)} x_e = 2 \quad \forall v \in V \\ & \sum_{e \in \delta(S)} x_e \geq 2 \quad \forall S \subset V, S \neq \emptyset \\ & x_e \in \{0, 1\} \quad \forall e \in E \end{array}$$

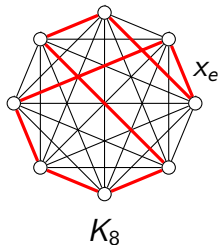
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- ▷ distances $d_e > 0$ for all $e \in E$

Binary variables

- ▷ $x_e = 1$ if edge e is used



$$\min \sum_{e \in E} d_e x_e$$

$$\text{subject to } \sum_{e \in \delta(v)} x_e = 2 \quad \forall v \in V \quad \text{node degree}$$

$$\sum_{e \in \delta(S)} x_e \geq 2 \quad \forall S \subset V, S \neq \emptyset$$

$$x_e \in \{0, 1\} \quad \forall e \in E$$

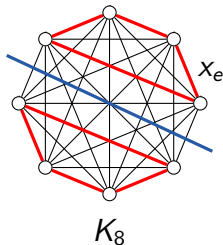
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Given

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$$\sum_{e \in \delta(S)} x_e \geq 2 \quad \forall S \subset V, S \neq \emptyset$$

subtour elimination

$$x_e \in \{0, 1\} \quad \forall e \in E$$

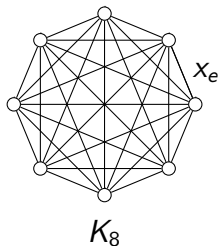
TSP – Integer Programming Formulation

Given

- ▷ complete graph $G = (V, E)$
- ▷ distances $d_e > 0$ for all $e \in E$

Binary variables

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$$\min \sum_{e \in E} d_e x_e$$

distance

$$\text{subject to } \sum_{e \in \delta(v)} x_e = 2$$

$$\forall v \in V$$

$$\sum_{e \in \delta(S)} x_e \geq 2$$

$$\forall S \subset V, S \neq \emptyset$$

$$x_e \in \{0, 1\}$$

$$\forall e \in E$$

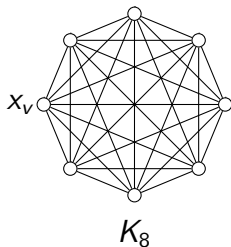
TSP – Constraint Programming Formulation

Given

- ▶ complete graph $G = (V, E)$
- ▶ for each $e \in E$ a distance $d_e > 0$

Integer variables

- ▶ x_v position of $v \in V$ in tour



TSP – Constraint Programming Formulation

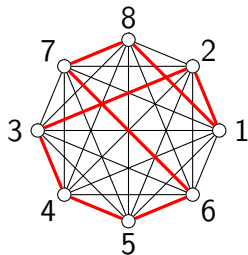
Given

- ▷ complete graph $G = (V, E)$
- ▷ for each $e \in E$ a distance $d_e > 0$

Integer variables

- ▷ x_v position of $v \in V$ in tour

$$\begin{array}{ll}\min & \text{length}(x_1, \dots, x_n) \\ \text{subject to} & \text{alldifferent}(x_1, \dots, x_n) \\ & x_v \in \{1, \dots, n\} \quad \forall v \in V\end{array}$$



What is a Constraint Integer Program?

Constraint Integer Program

Objective function:

- ▷ linear function

Feasible set:

- ▷ described by arbitrary constraints

Variable domains:

- ▷ real or integer values

When no more branching possible:

- ▷ CIP becomes an LP/NLP

$$\begin{array}{ll}\min & c^T x \\ \text{s.t.} & x \in F \\ & (x_I, x_C) \in \mathbb{Z}^I \times \mathbb{R}^C\end{array}$$

Remark:

- ▷ arbitrary objective or variables modeled by constraints

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Constraint Integer Program

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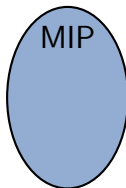
▷ CIP becomes an LP/NLP

$$\begin{array}{ll} \min & \sum_{e \in E} d_e x_e \\ \text{s.t.} & \sum_{e \in \delta(v)} x_e = 2 \quad \forall v \in V \\ & \text{nosubtour}(x) \\ & x_e \in \{0, 1\} \quad \forall e \in E \end{array}$$

(CIP formulation of TSP)

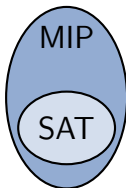
Single nosubtour constraint rules out subtours (e.g. by domain propagation). It may also separate subtour elimination inequalities.

▷ Mixed Integer Programs



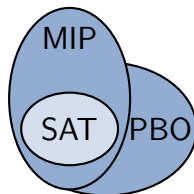
Constraint Integer Programming

- ▷ Mixed Integer Programs
- ▷ SATisifiability problems



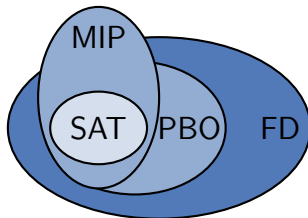
Constraint Integer Programming

- ▷ Mixed Integer Programs
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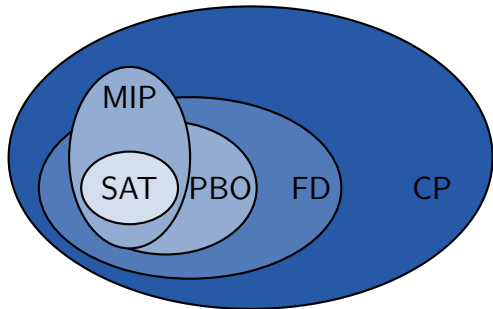
Constraint Integer Programming

- ▷ Mixed Integer Programs
- ▷ SATisfiability problems
- ▷ Pseudo-Boolean Optimization
- ▷ Finite Domain



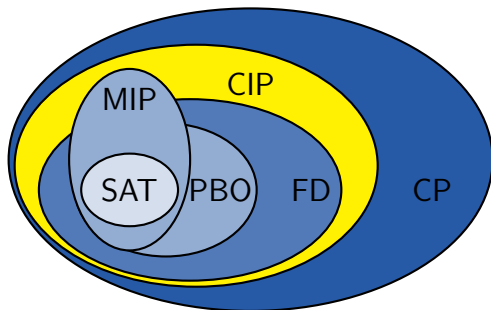
Constraint Integer Programming

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- ▷ Finite Domain
- ▷ Constraint Programming



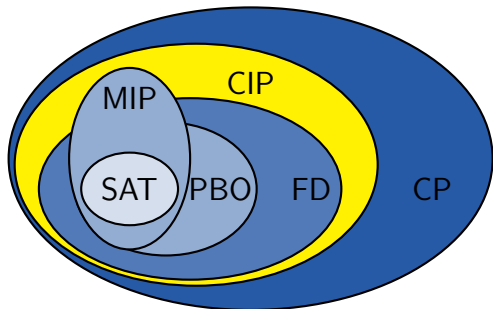
Constraint Integer Programming

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Constraint Integer Programming

- ▷ Mixed Integer Programs
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- ▷ Finite Domain
- ▷ Constraint Programming
- ▷ Constraint Integer Programming



Relation to CP and MIP

- ▷ Every MIP is a CIP. " $MIP \subsetneq CIP$ "
- ▷ Every CP over a finite domain space is a CIP. " $FD \subsetneq CIP$ "

SCIP – Solving Constraint Integer Programs

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- 2 Solving Constraint Integer Programs
- 3 The Solving Process of SCIP

<http://scip.zib.de>

MIP

- ▷ LP relaxation
- ▷ cutting planes

CP

- ▷ domain propagation

SAT

- ▷ conflict analysis
- ▷ periodic restarts

MIP, CP, and SAT

- ▷ branch-and-bound

The diagram illustrates the architecture of the SCIP solver. On the left, three boxes represent specialized solvers: MIP (Mixed Integer Programming), CP (Constraint Programming), and SAT (Satisfiability). Each box lists its core techniques. On the right, a box represents the integration of these solvers into a branch-and-bound framework. Arrows from each of these four boxes point towards a central yellow circle labeled 'SCIP', indicating that SCIP is the central engine that coordinates and integrates these different solving techniques.

SCIP

SCIP (Solving Constraint Integer Programs) ...

- ▷ provides a full-scale MIP and MINLP solver,
- ▷ is constraint based,
- ▷ incorporates
 - ▶ CP features (domain propagation),
 - ▶ MIP features (cutting planes, LP relaxation), and
 - ▶ SAT-solving features (conflict analysis, restarts),
- ▷ is a branch-cut-and-price framework,
- ▷ has a modular structure via plugins,
- ▷ is free for academic purposes,
- ▷ and is available in source-code under <http://scip.zib.de> !

▷ interface and usability

- ▶ user-friendly interactive shell
- ▶ interfaces to AMPL, GAMS, ZIMPL, MATLAB, Python and Java
- ▶ C++ wrapper classes
- ▶ LP solvers: CLP, CPLEX, Gurobi, MOSEK, QSOpt, SoPlex, Xpress
- ▶ over 1 600 parameters and 15 emphasis settings

▷ documentation and guidelines

- ▶ more than 450 000 lines of C code, 20% documentation
 - ▶ 30 000 assertions, 4 000 debug messages
- ▶ HowTos: plugins types, debugging, automatic testing
- ▶ 11 examples illustrating the use of SCIP
- ▶ active mailing list (280 members)

▷ about 5000 downloads per year

- ▷ Toolbox for **generating** and **solving** constraint integer programs
- ▷ free for academic use, available in source code

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ZIMPL

- ▷ model and generate LPs, MIPs, and MINLPs

SCIP

- ▷ MIP, MINLP and CIP solver, branch-cut-and-price framework

SoPlex

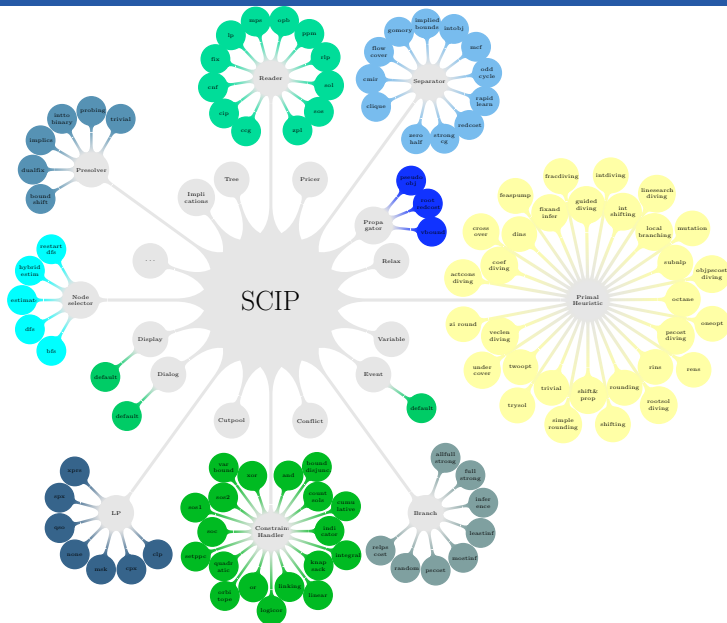
- ▷ revised primal and dual simplex algorithm

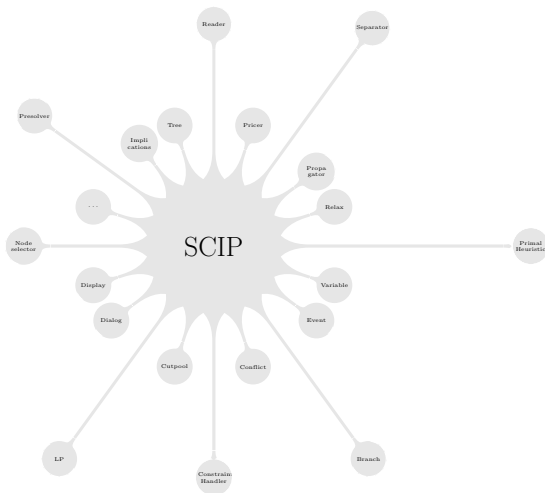
GCG → see talk tomorrow 9:40

- ▷ generic branch-cut-and-price solver

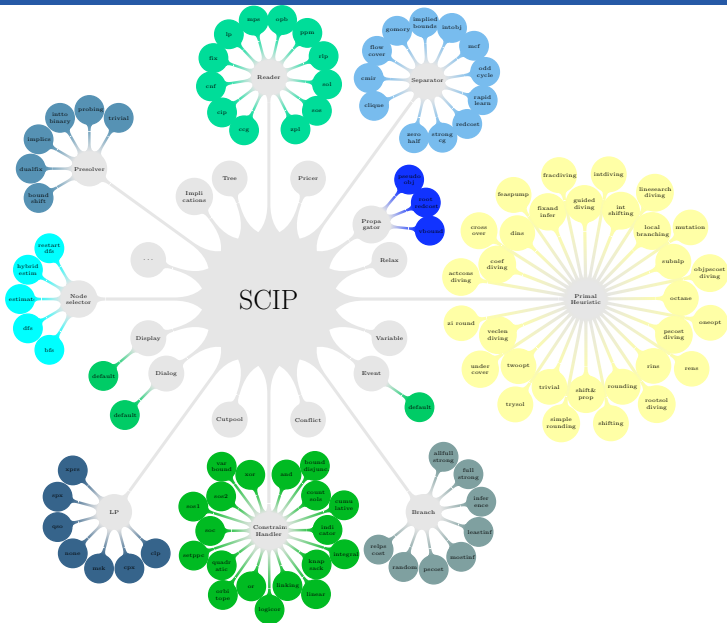
UG → see talk tomorrow 10:20

- ▷ framework for parallelization of MIP and MINLP solvers





Structure of SCIP



SCIP core

- ▷ branching tree
- ▷ variables
- ▷ conflict analysis
- ▷ solution pool
- ▷ cut pool
- ▷ statistics
- ▷ clique table
- ▷ implication graph
- ▷ ...

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Plugins

- ▷ external callback objects
- ▷ interact with the framework through a very detailed interface

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- ▷ external callback objects
 - ▷ interact with the framework through a very detailed interface
 - ▷ SCIP knows for each plugin type:
 - ▶ the number of available plugins
 - ▶ priority defining the calling order (usually)
 - ▷ SCIP does not know any structure behind a plugin
- ⇒ plugins are black boxes for the SCIP core

SCIP core

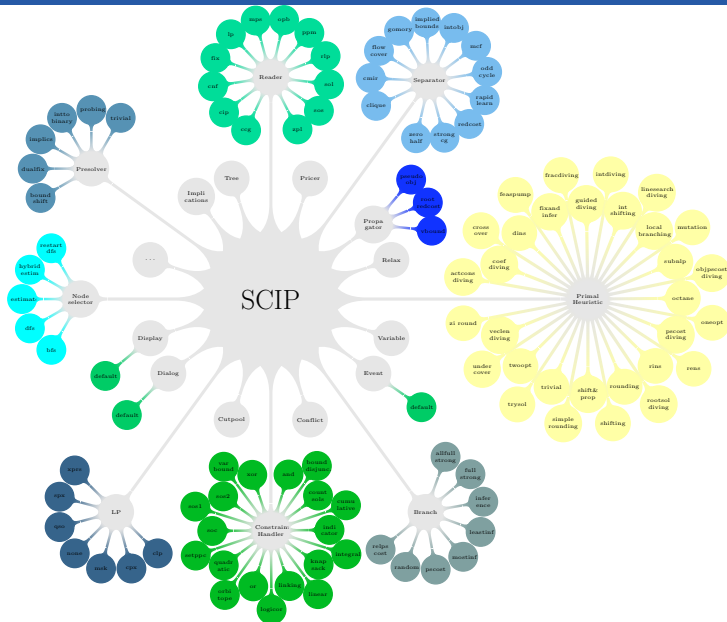
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Plugins

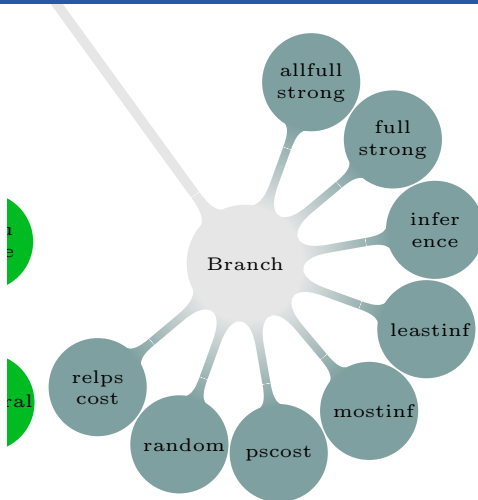
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- ⇒ plugins are black boxes for the SCIP core
- ⇒ Very flexible branch-and-bound based search algorithm

- ▷ **Constraint handler:** assures feasibility, strengthens formulation
- ▷ **Separator:** adds cuts, improves dual bound
- ▷ **Pricer:** allows dynamic generation of variables
- ▷ **Heuristic:** searches solutions, improves primal bound
- ▷ **Branching rule:** how to divide the problem?
- ▷ **Node selection:** which subproblem should be regarded next?
- ▷ **Presolver:** simplifies the problem in advance, strengthens structure
- ▷ **Propagator:** simplifies problem, improves dual bound locally
- ▷ **Reader:** reads problems from different formats
- ▷ **Event handler:** catches events (e.g., bound changes, new solutions)
- ▷ **Display:** allows modification of output
- ▷ ...

A closer look: branching rules



A closer look: branching rules



What does SCIP know about branching rules?

- ▷ SCIP knows **the number of** available **branching rules**
- ▷ each branching rule has a **priority**
- ▷ SCIP calls the branching rule in decreasing order of priority
- ▷ the interface defines the **possible results** of a call:
 - ▶ branched
 - ▶ reduced domains
 - ▶ added constraints
 - ▶ detected cutoff
 - ▶ did not run

How does SCIP call a branching rule?

```
/* start timing */
SCIPclockStart(branchrule->branchclock, set);

/* call external method */
SCIP_CALL( branchrule->branchexeclp(set->scip, branchrule,
    allowaddcons, result) );

/* stop timing */
SCIPclockStop(branchrule->branchclock, set);

/* evaluate result */
if( *result != SCIP_CUTOFF
    && *result != SCIP_CONSADDED
    && *result != SCIP_REDUCEDDOM
    && *result != SCIP_SEPARATED
    && *result != SCIP_BRANCHED
    && *result != SCIP_DIDNOTRUN )
{
    SCIPerrorMessage(
        "branching rule %s returned invalid result code %d from LP\n",
        solution, branching,
        branchrule->name, *result);
    return SCIP_INVALIDRESULT;
}
```

Plugins are allowed to access all global (core) information

- ▷ branching tree
- ▷ variables
- ▷ conflict analysis
- ▷ solution pool
- ▷ cut pool
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Ideally, plugins should not access data of other plugins!!!

What can a plugin access?

Plugins are allowed to access all global (core) information

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Ideally, plugins should not access data of other plugins!!!

Branching Rules

- ▷ LP solution
- ▷ variables
- ▷ statistics

Constraint handlers

- ▷ most powerful plugins in SCIP
- ▷ define the feasible region
- ▷ a single constraint may represent a whole set of inequalities

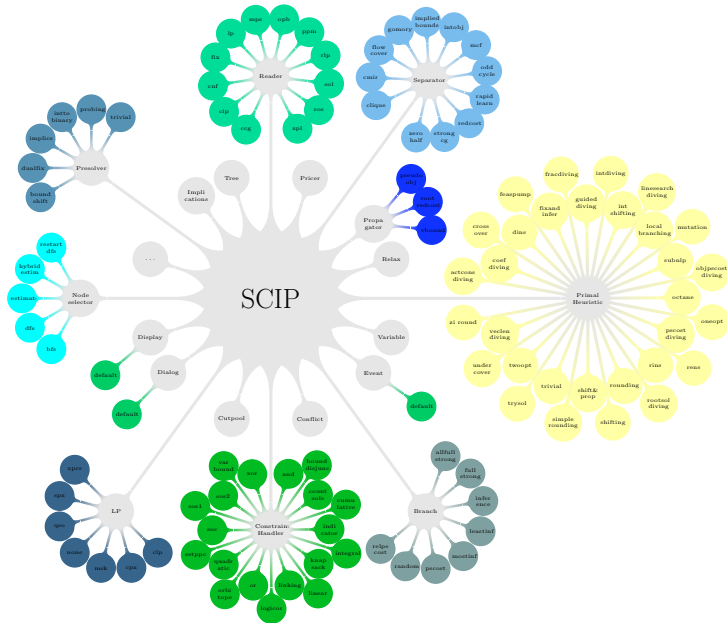
Functions

- ▷ check and enforce feasibility of solutions
- ▷ can add linear representation to LP relaxation
- ▷ constraint-specific presolving, domain propagation, separation

Result

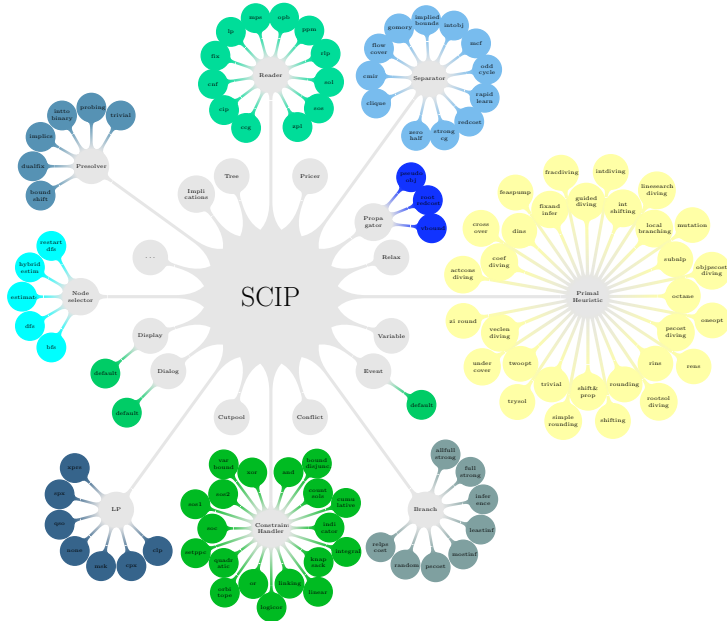
- ▷ SCIP is **constraint based**
 - ▶ Advantage: flexibility
 - ▶ Disadvantage: limited global view

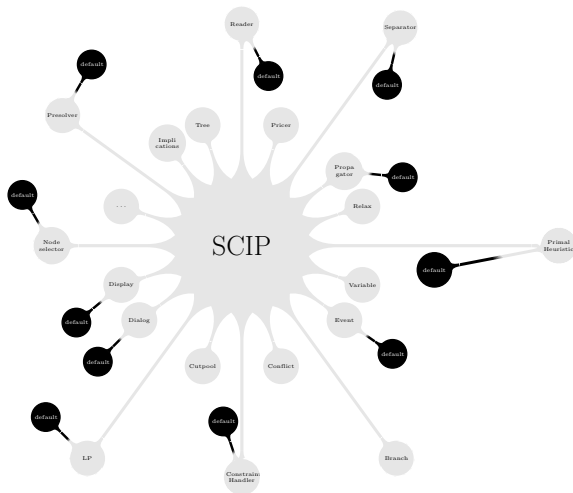
Default Plugins

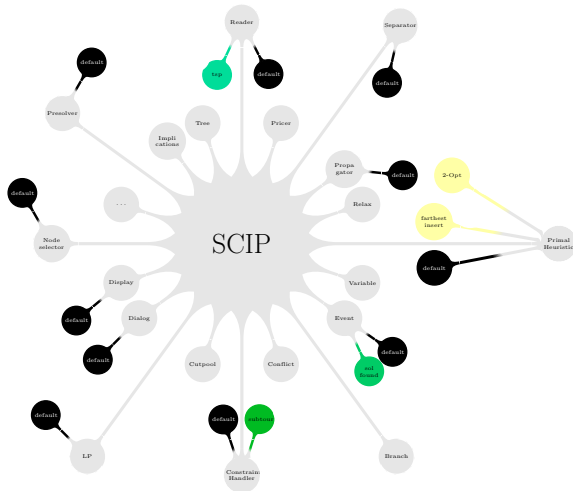


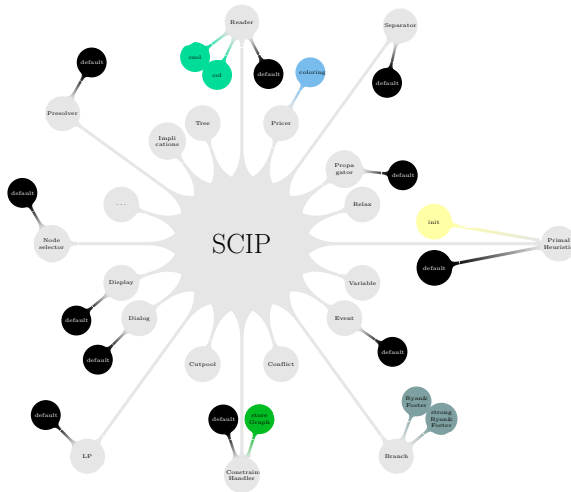
Number of default plugins

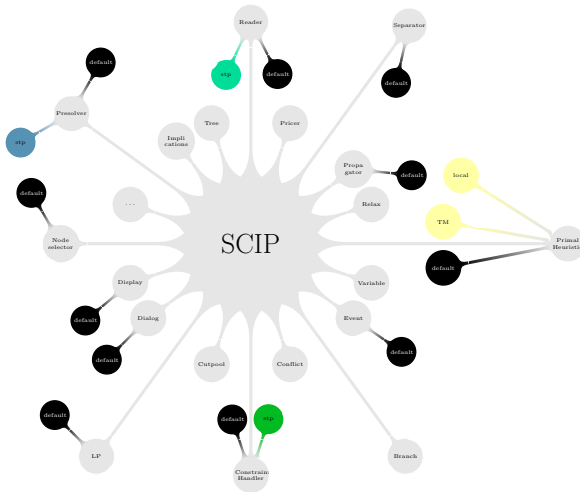
Plugin	SCIP Version									
	0.7	0.8	0.9	1.0	1.1	1.2	2.0	2.1	3.0	3.1
Branching Rules	6	7	8	8	8	8	8	8	8	9
Constraint Handlers	10	10	11	11	14	16	23	25	26	26
Node Selectors	3	7	3	5	5	5	5	5	5	7
Presolvers	2	7	5	5	6	6	6	5	9	9
Primal Heuristics	9	14	21	23	24	27	31	33	35	38
Propagators	0	1	2	2	2	2	3	5	7	8
Readers	2	4	6	6	11	13	15	16	17	18
Separators	3	6	7	8	10	10	12	13	13	13









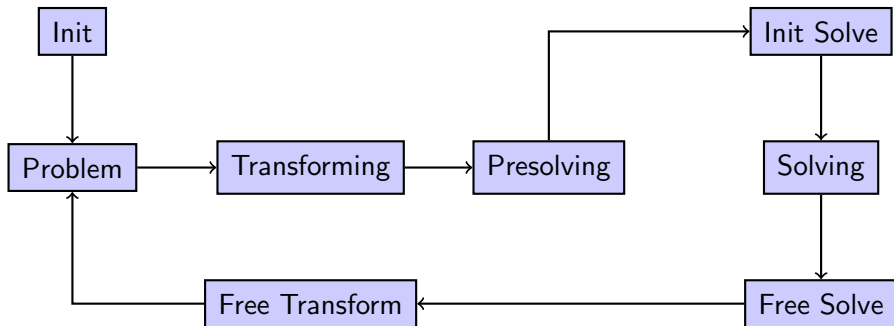


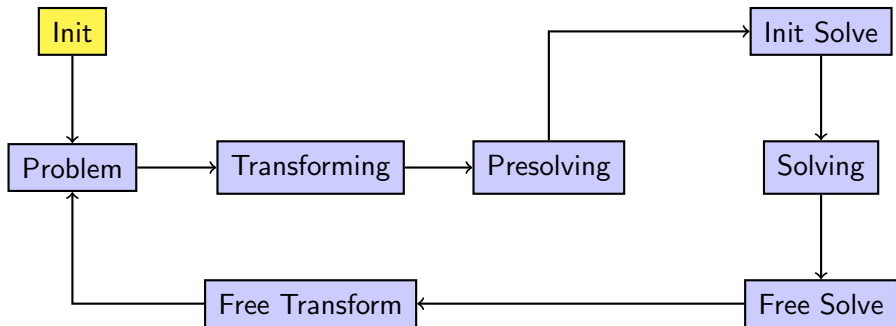
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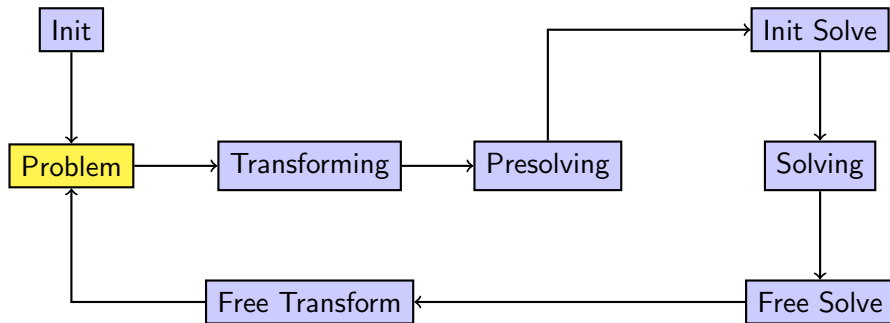
<http://scip.zib.de>

Operational Stages





- ▷ Basic data structures are allocated and initialized.
- ▷ User includes required plugins (or just takes default plugins).



- ▷ User creates and modifies the original problem instance.
- ▷ Problem creation is usually done in file readers.

Define Variables (TSP Example)

```
SCIP_VAR* var;
SCIP_CALL(                                     // return value macro
    SCIPcreateVar(
        scip,                                // SCIP pointer
        &var,                                // save in variable
        "varname",                           // pass variable name
        0.0,                                 // lower bound
        1.0,                                 // upper bound
        length,                              // obj. value
        SCIP_VARTYPE_BINARY,                 // type
        TRUE,                                // initial
        FALSE,                               // removable
        NULL, NULL, NULL,                   // no callback functions
        NULL                                 // no variable data
    )
);
SCIP_CALL( SCIPaddVar(scip, var) );           // add var.
```

Define Variables (TSP Example)

```
SCIP_VAR* var;
SCIP_CALL(                                     // return value macro
    SCIPcreateVarBasic(
        scip,                                 // SCIP pointer
        &var,                                 // save in variable
        "varname",                           // pass variable name
        0.0,                                 // lower bound
        1.0,                                 // upper bound
        length,                              // obj. value
        SCIP_VARTYPE_BINARY                  // type
    )
);
SCIP_CALL( SCIPaddVar(scip, var) );           // add var.
```

TSP: Define Degree Constraints

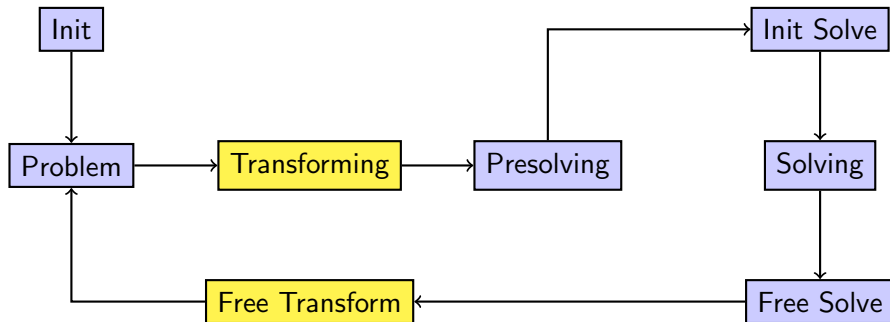
```
SCIP_CALL( SCIPcreateConsLinear(  
    scip,           // SCIP pointer  
    &cons,          // save in cons  
    "consname",     // name  
    nvar,           // number of variables  
    vars,           // array of variables  
    vals,           // array of values  
    2.0,            // left hand side  
    2.0,            // right hand side (equation)  
    TRUE,           // initial?  
    FALSE,          // separate?  
    TRUE,           // enforce?  
    TRUE,           // check?  
    TRUE,           // propagate?  
    FALSE,          // local?  
    FALSE,          // modifiable?  
    FALSE,          // dynamic?  
    FALSE,          // removable?  
    FALSE           // stick at node?  
    ) );  
SCIP_CALL( SCIPaddCons(scip, cons) );           // add constraint  
SCIP_CALL( SCIPreleaseCons(scip, &cons) );     // free cons. space
```

MIPs are specified using linear constraints only (may be “upgraded”).

TSP: Define Degree Constraints

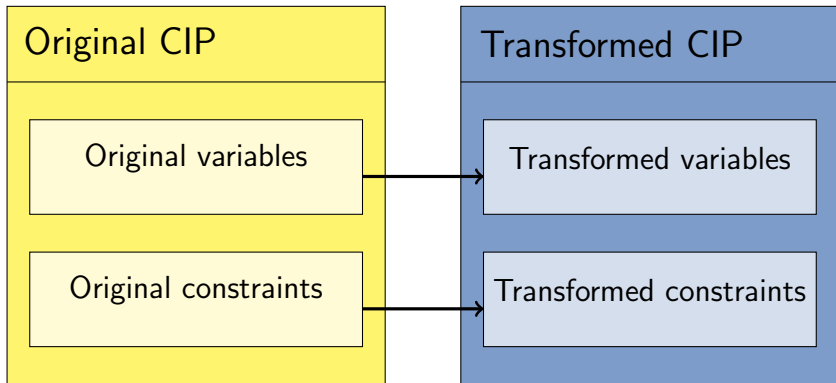
```
SCIP_CALL( SCIPcreateConsBasicLinear(  
    scip,           // SCIP pointer  
    &cons,           // save in cons  
    "consname",     // name  
    nvar,           // number of variables  
    vars,           // array of variables  
    vals,           // array of values  
    2.0,            // left hand side  
    2.0             // right hand side (equation)  
) );  
SCIP_CALL( SCIPaddCons(scip, cons) );           // add constraint  
SCIP_CALL( SCIPreleaseCons(scip, &cons) );     // free cons. space
```

MIPs are specified using linear constraints only (may be “upgraded”).

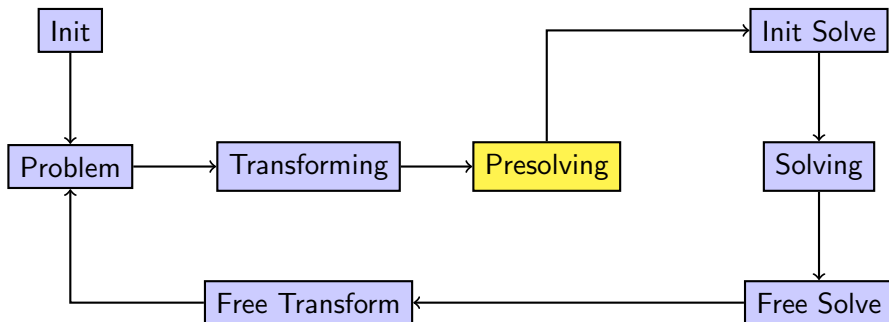


- Creates a working copy of the original problem.

Original and Transformed Problem

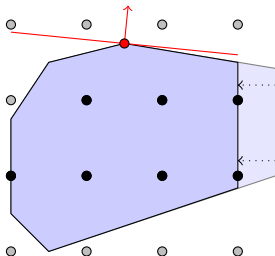


- ▷ data is copied into separate memory area
- ▷ presolving and solving operate on transformed problem
- ▷ original data can only be modified in problem modification stage



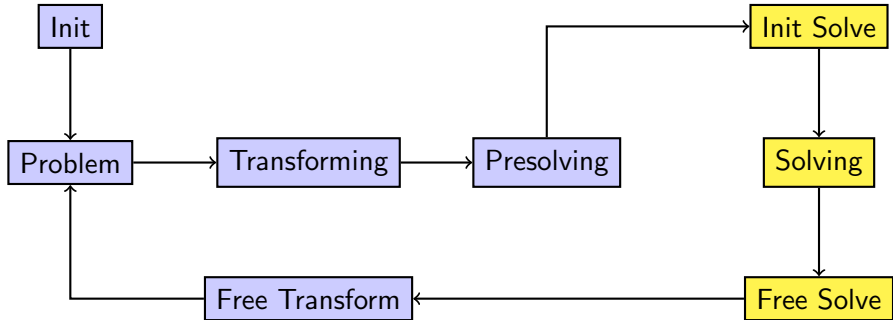
Task

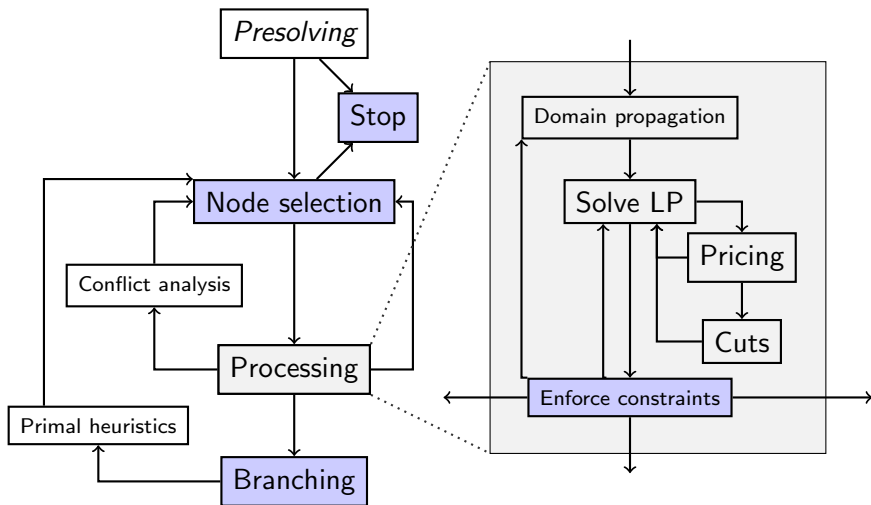
- ▷ reduce size of model by removing irrelevant information
- ▷ strengthen LP relaxation by exploiting integrality information
- ▷ make the LP relaxation numerically more stable
- ▷ extract useful information

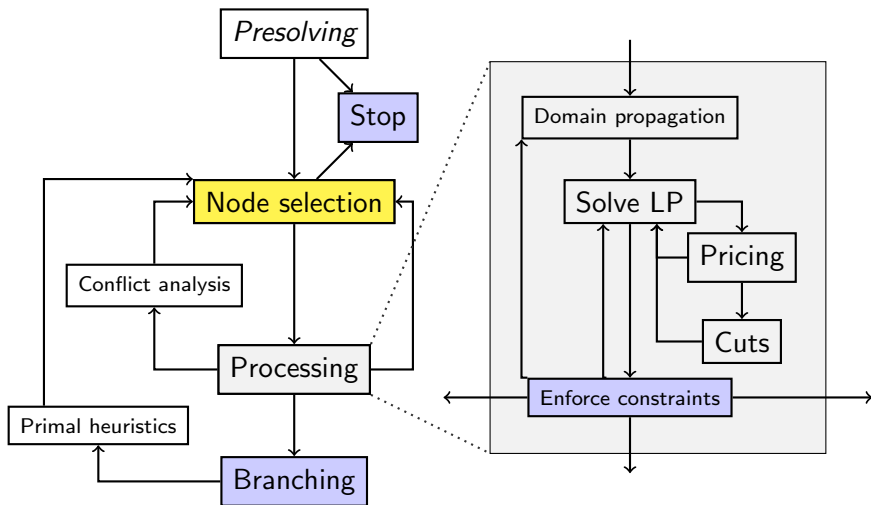


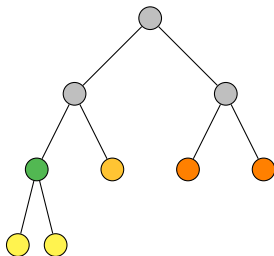
Primal Reductions: ▷ based on feasibility reasoning
▷ no feasible solution is cut off

Dual Reductions: ▷ consider objective function
▷ at least one optimal solution remains







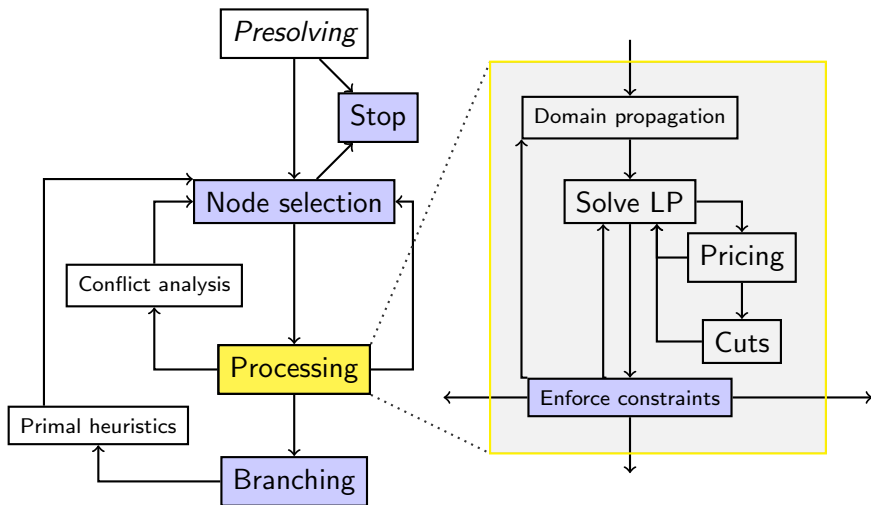


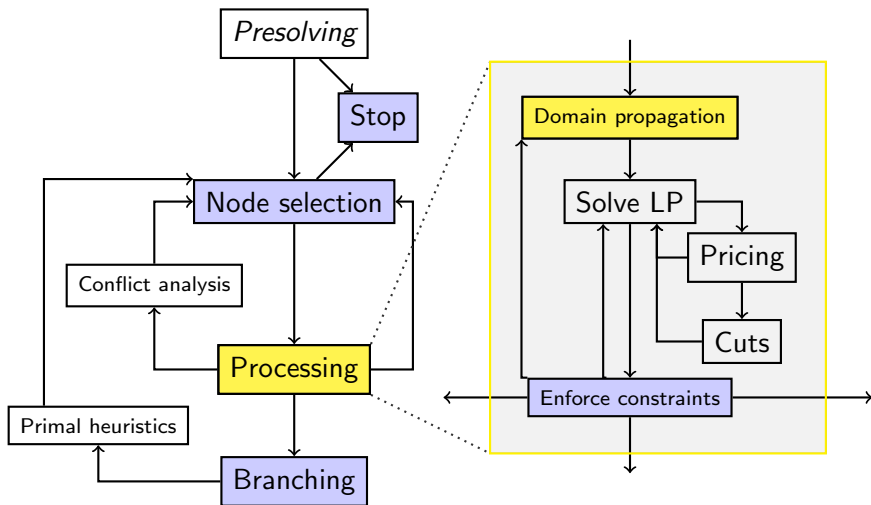
Task

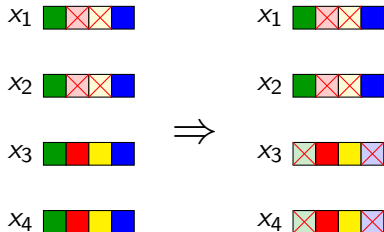
- ▷ improve primal bound
- ▷ keep comp. effort small
- ▷ improve global dual bound

Techniques

- ▷ **basic rules**
 - ▶ depth first search (DFS)
 - early feasible solutions
 - ▶ best bound search (BBS)
 - improve dual bound
 - ▶ best estimate search (BES)
 - improve primal bound
- ▷ **combinations**
 - ▶ BBS or BES with plunging
 - ▶ hybrid BES/BBS
 - ▶ interleaved BES/BBS





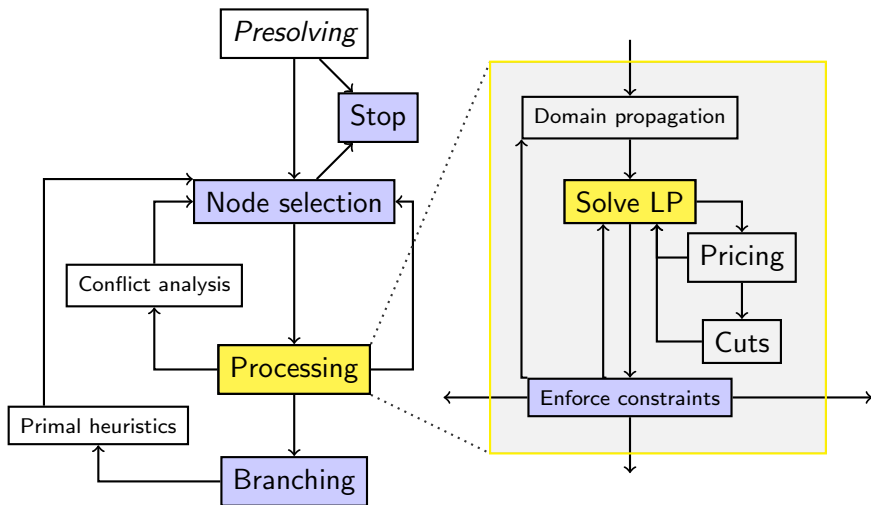


Task

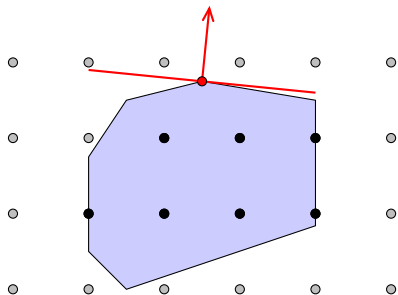
- ▷ simplify model locally
- ▷ improve local dual bound
- ▷ detect infeasibility

Techniques

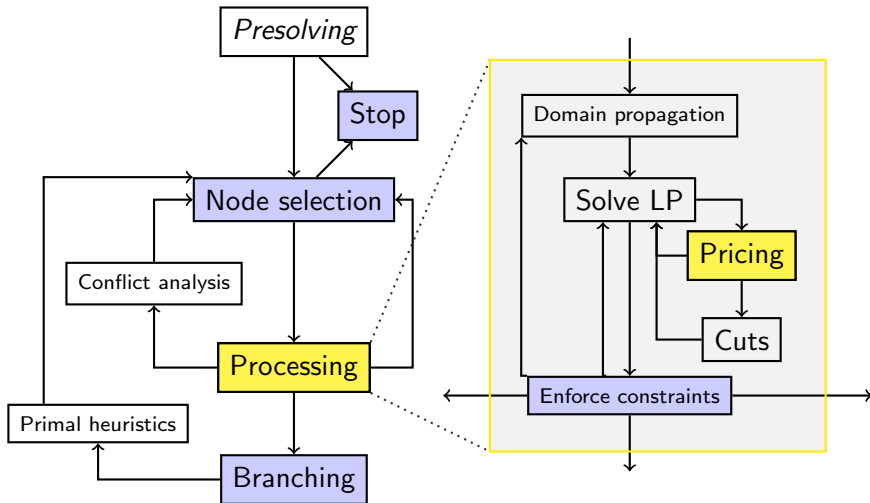
- ▷ **constraint specific**
 - ▶ each cons handler may provide a propagation routine
 - ▶ reduced presolving (usually)
- ▷ **dual propagation**
 - ▶ root reduced cost strengthening
 - ▶ objective function
- ▷ **special structures**
 - ▶ variable bounds

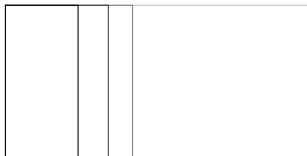


- ▷ LP solver is a black box
- ▷ interface to different LP solvers:
SoPlex, CPLEX, XPress,
Gurobi, CLP, ...
- ▷ primal/dual simplex
- ▷ barrier with/without crossover



- ▷ feasibility double-checked by SCIP
- ▷ condition number check
- ▷ resolution by changing parameters:
scaling, tolerances, solving from scratch, other simplex



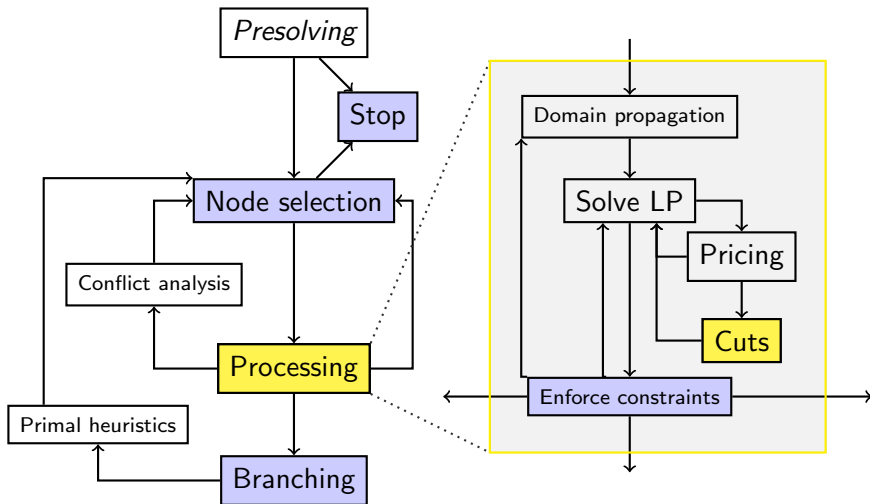


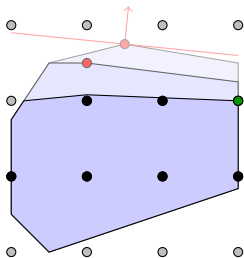
Branch-and-Price

- ▷ huge number of variables
- ▷ start with subset
- ▷ add others, when needed

Pricing

- ▷ find variable with negative reduced costs
- ▷ or prove that there exists none
- ▷ typically problem specific
- ▷ dynamic aging of variables
- ▷ problem variable pricer to add them again
- ▷ early branching possible
- ▷ lazy variable bounds



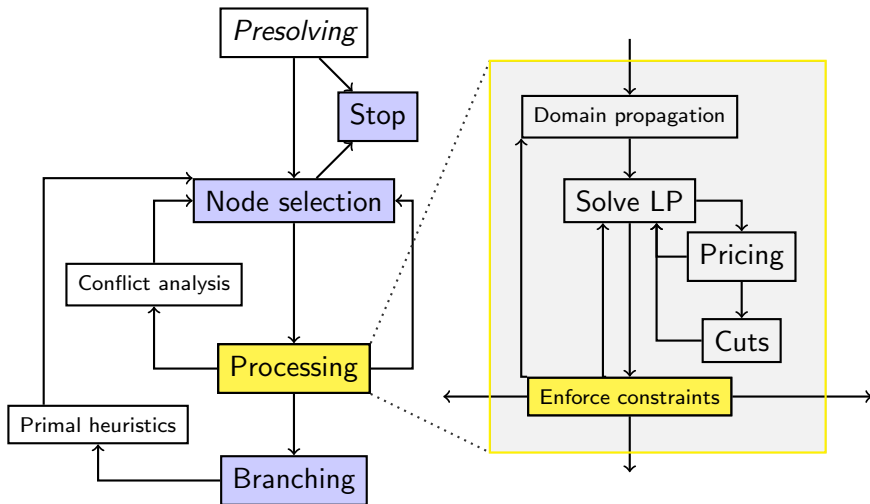


Task

- ▷ strengthen relaxation
- ▷ add valid constraints
- ▷ generate on demand

Techniques

- ▷ **general cuts**
 - ▶ complemented MIR cuts
 - ▶ Gomory mixed integer cuts
 - ▶ strong Chvátal-Gomory cuts
 - ▶ implied bound cuts
 - ▶ reduced cost strengthening
- ▷ **problem specific cuts**
 - ▶ 0-1 knapsack problem
 - ▶ stable set problem
 - ▶ 0-1 single node flow problem



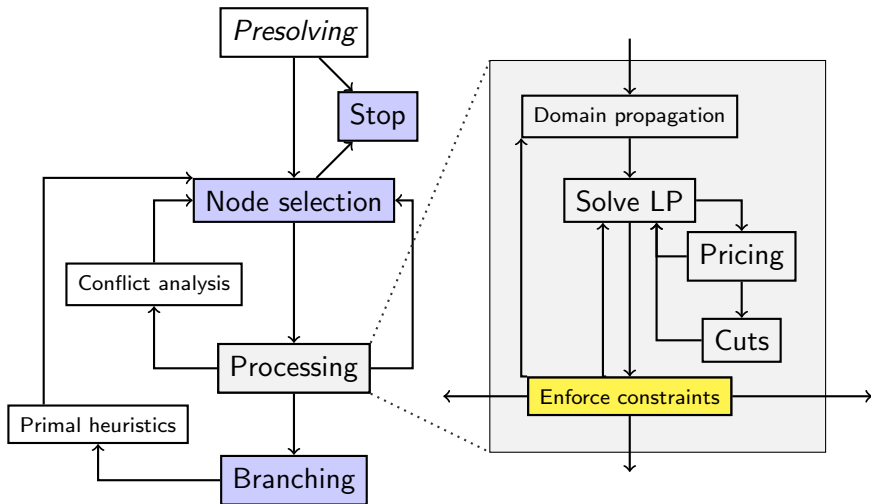
LP solution may violate a constraint not contained in the relaxation.

Enforcing is necessary for a correct implementation!

Constraint handler resolves the infeasibility by ...

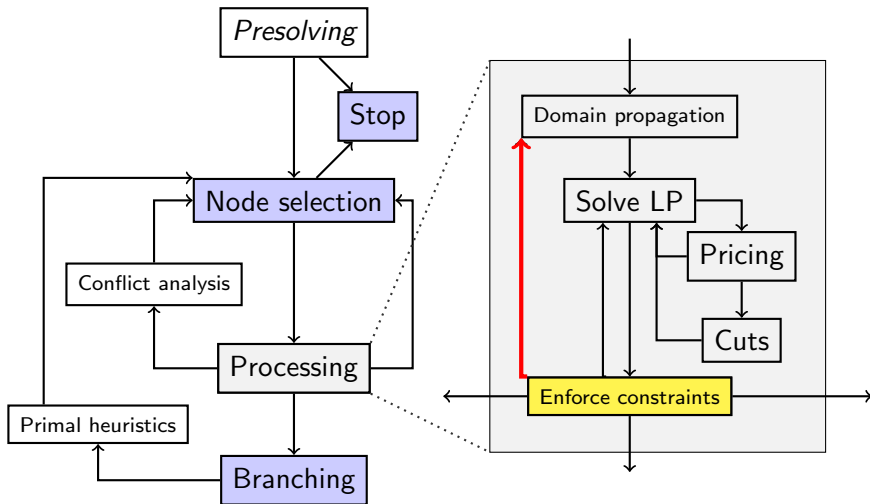
- ▷ Reducing a variable's domain,
- ▷ Separating a cutting plane (may use integrality),
- ▷ Adding a (local) constraint,
- ▷ Creating a branching,
- ▷ Concluding that the subproblem is infeasible and can be cut off, or
- ▷ Just saying “solution infeasible”.

Constraint Enforcement



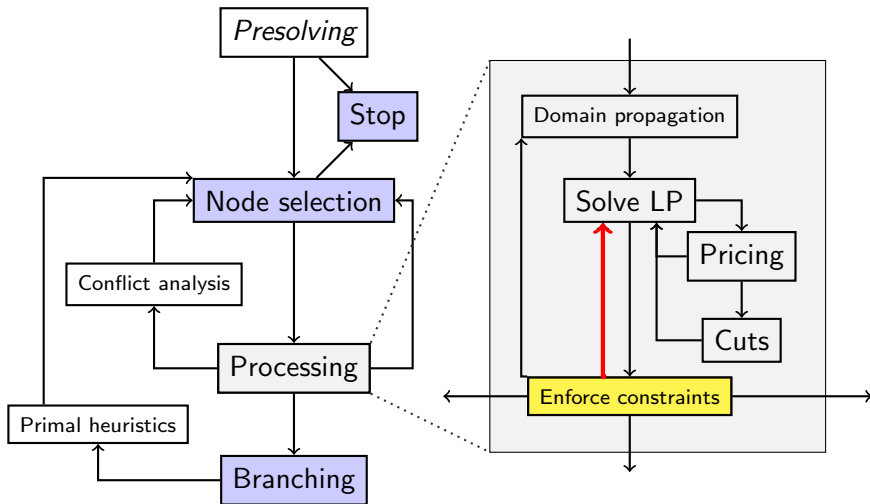
- ▷ Reduced domain
- ▷ Added cut
- ▷ Cutoff
- ▷ Infeasible
- ▷ Added constraint
- ▷ Branched
- ▷ Feasible

Constraint Enforcement



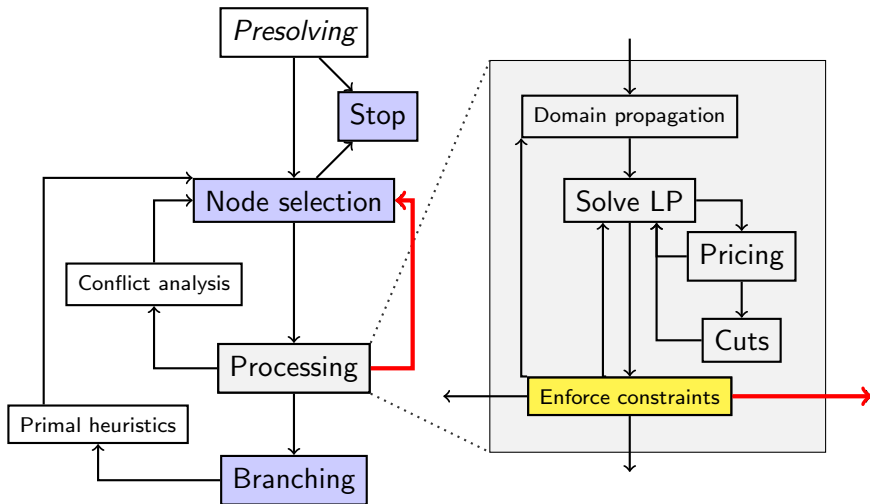
- ▷ Reduced domain
- ▷ Added cut
- ▷ Cutoff
- ▷ Infeasible
- ▷ Added constraint
- ▷ Branched
- ▷ Feasible

Constraint Enforcement



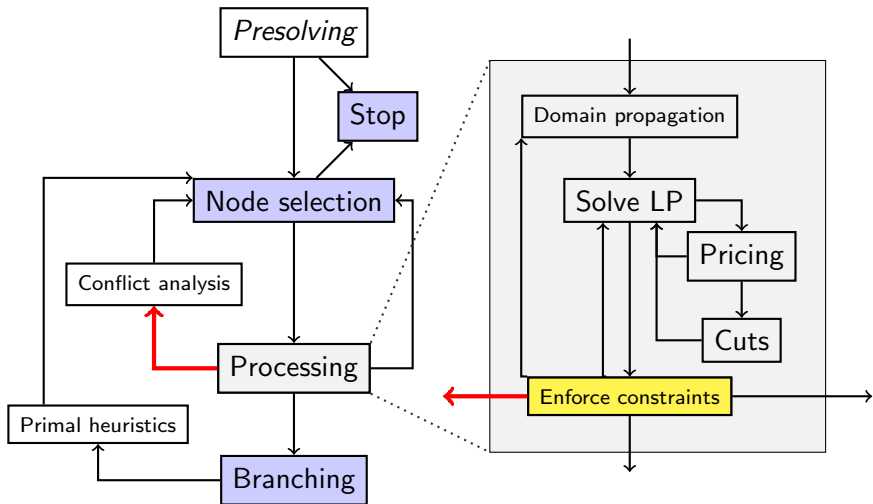
- ▷ Reduced domain
- ▷ Added constraint
- ▷ Added cut
- ▷ Branched
- ▷ Cutoff
- ▷ Infeasible
- ▷ Feasible

Constraint Enforcement



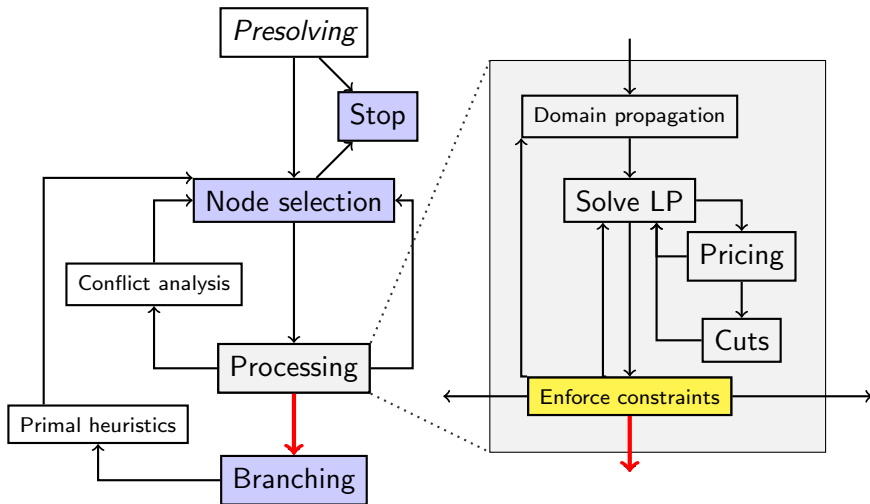
- ▷ Reduced domain
- ▷ Added cut
- ▷ Cutoff
- ▷ Infeasible
- ▷ Added constraint
- ▷ Branched
- ▷ Feasible

Constraint Enforcement



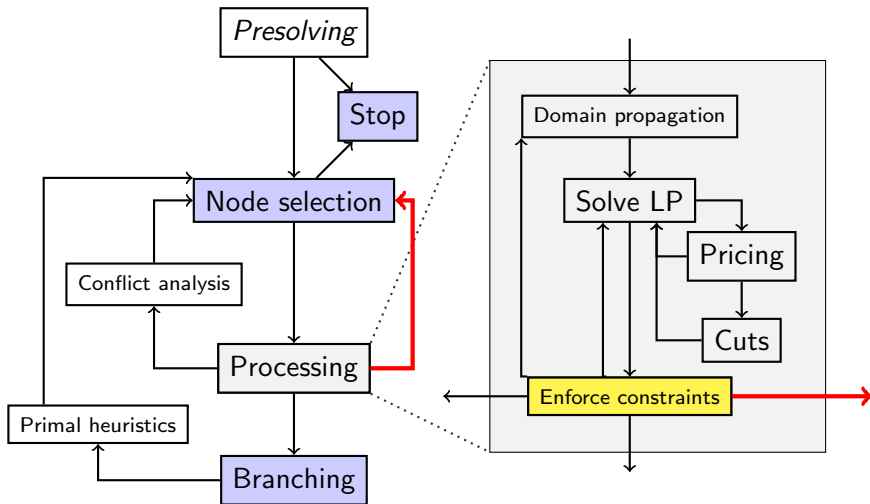
- ▷ Reduced domain
- ▷ Added cut
- ▷ **Cutoff**
- ▷ Infeasible
- ▷ Added constraint
- ▷ Branched
- ▷ Feasible

Constraint Enforcement

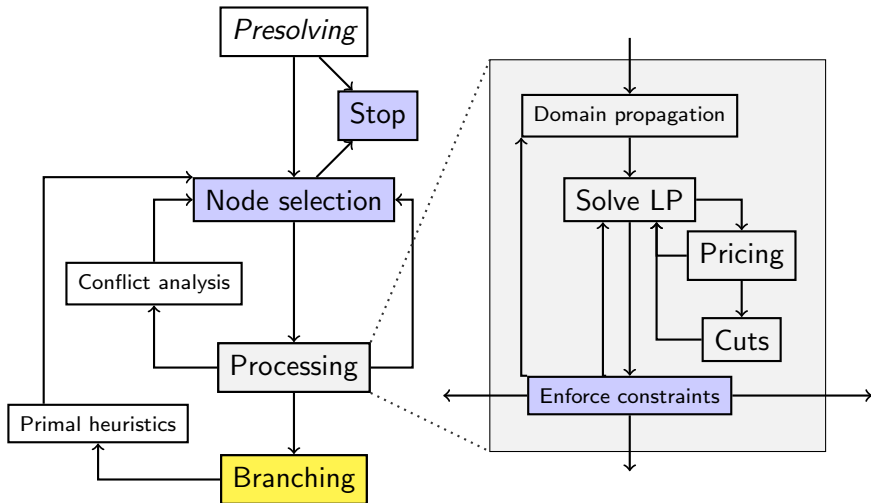


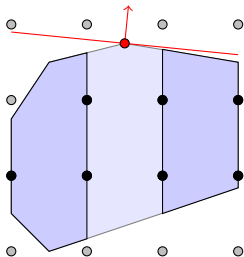
- ▷ Reduced domain
- ▷ Added cut
- ▷ Cutoff
- ▷ Infeasible
- ▷ Added constraint
- ▷ Branched
- ▷ Feasible

Constraint Enforcement



- ▷ Reduced domain
- ▷ Added cut
- ▷ Cutoff
- ▷ Infeasible
- ▷ Added constraint
- ▷ Branched
- ▷ Feasible



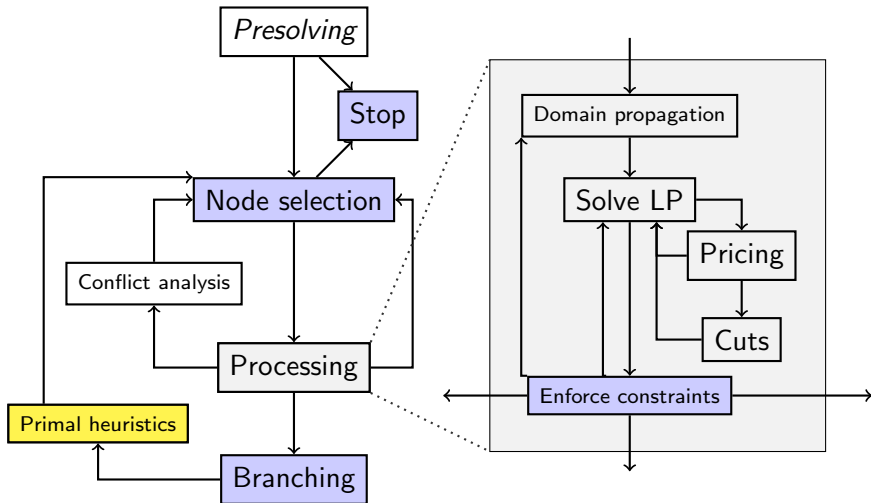


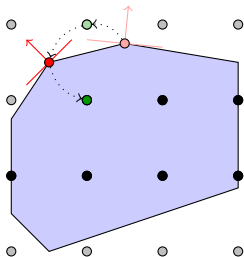
Task

- ▷ divide into (disjoint) subproblems
- ▷ improve local bounds

Techniques

- ▷ branching on variables
 - ▶ most infeasible
 - ▶ least infeasible
 - ▶ random branching
 - ▶ strong branching
 - ▶ pseudocost
 - ▶ reliability
 - ▶ VSIDS
 - ▶ hybrid reliability/inference
- ▷ branching on constraints
 - ▶ SOS1
 - ▶ SOS2



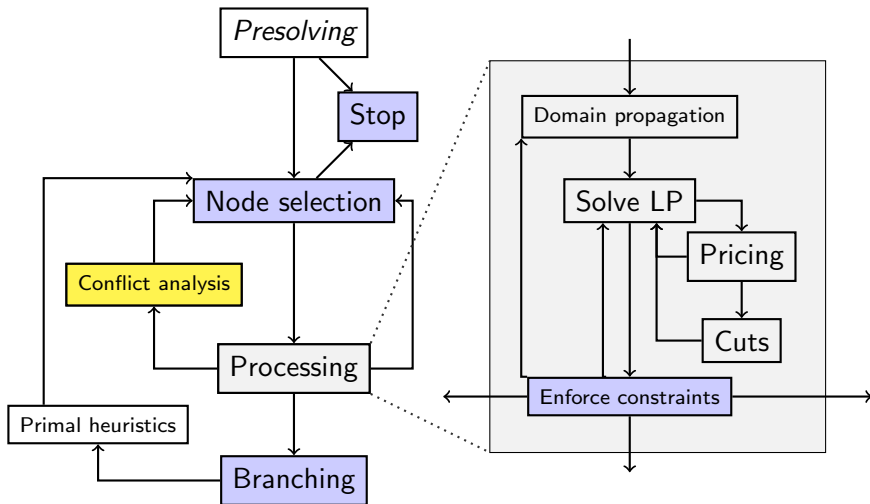


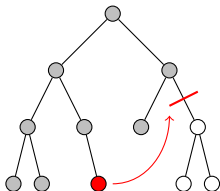
Task

- ▷ improve primal bound
- ▷ effective on average
- ▷ guide remaining search

Techniques

- ▷ rounding
 - ▶ possibly solve final LP
- ▷ diving
 - ▶ least infeasible
 - ▶ guided
- ▷ objective diving
 - ▶ objective feasibility pump
- ▷ Large Neighborhood Search
 - ▶ RINS, local branching
 - ▶ RENS
- ▷ combinatorial



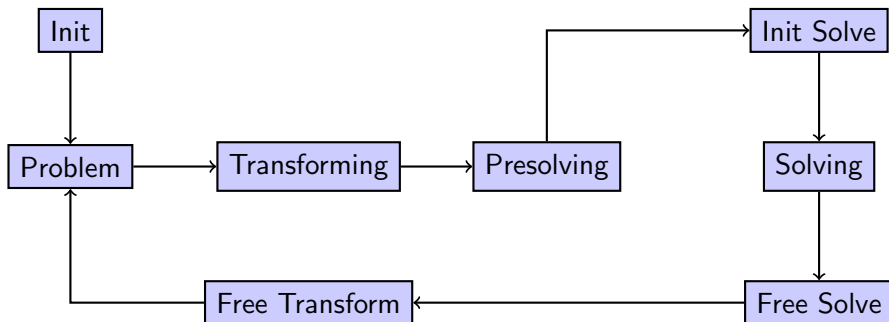


Task

- ▷ Analyze infeasibility
- ▷ Derive valid constraints
- ▷ Help to prune other nodes

Techniques

- ▷ **Analyze:**
 - ▶ Propagation conflicts
 - ▶ Infeasible LPs
 - ▶ Bound-exceeding LPs
 - ▶ Strong branching conflicts
- ▷ **Detection:**
 - ▶ Cut in conflict graph
 - ▶ LP: Dual ray heuristic
- ▷ **Use conflicts:**
 - ▶ Only for propagation
 - ▶ As cutting planes



- ▷ SCIP has own memory handling.
 - ▶ Standard memory: `SCIPAllocMemoryArray(scip,&p,10),`
`SCIPfreeMemoryArray(scip,&p)`
 - ▶ Block memory: `SCIPAllocBlockMemoryArray(scip,&p,10),`
`SCIPfreeBlockMemoryArray(scip,&p,10)`
 - ▶ Fast buffer: `SCIPAllocBufferArray(scip,&p,10),`
`SCIPfreeBufferArray(scip,&p)`
- ▷ Functions calling `SCIP_RETCODE <function>()` should use the `SCIP_CALL()` macro and should return `SCIP_RETCODE`.
- ▷ There are template files, e.g. `cons_xyz.{c,h}`.
- ▷ Only include `scip/scip.h`, `pub_*.h`, or `scip/scipdefplugins.h`.

- ▷ [Constraint Integer Programming](#)
Ph.D. dissertation of Tobias Achterberg, 2007.
- ▷ [Solving mixed integer linear and nonlinear problems using the SCIP Optimization Suite](#)
ZIB Report, 2012.
- ▷ <http://scip.zib.de>
Doxygen documentation, HowTos, FAQ
- ▷ See: `scip.h`, `pub_*.h`, `<plugin>.h` (e.g. `cons_linear.h`)
- ▷ If nothing helps: SCIP mailing list (scip@zib.de)

SCIP is...

- ▷ a solver for MIP and MINLP
- ▷ a framework for branch-and-bound based algorithms (branch-and-cut, branch-and-price, ...)
- ▷ part of the SCIP Optimization Suite

Advantages of SCIP:

- ▷ broad scope (→ next two days)
- ▷ available in source code (→ coming next)
- ▷ actively developed (→ tomorrow)
- ▷ hundreds of parameters to play with (→ afternoon)
- ▷ easily extendable (→ afternoon)

09:00 – 10:30	Introduction and Overview
10:30 – 11:00	Coffee Break
11:00 – 12:30	Installation and Testing Environment
12:30 – 14:00	Lunch Break
14:00 – 15:00	Parameter Tuning
15:00 – 15:30	Coffee Break
15:30 – 17:30	Programming Exercise

WiFi:

- ▷ eduroam
- ▷ “Gast im ZIB” (no password)