

# Cutting Planes and Primal Heuristics

CO@Work Berlin

Timo Berthold and Kati Wolter

09/30/2009



**DFG Research Center MATHEON**  
Mathematics for key technologies



# Cutting Planes and Primal Heuristics

CO@Work Berlin

Timo Berthold and Kati Wolter

09/30/2009



Berlin  
Mathematical  
School



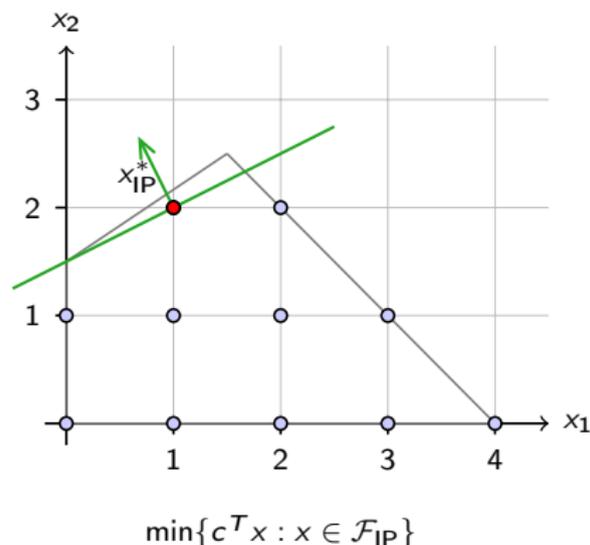
DFG Research Center MATHEON  
Mathematics for key technologies



# General Cutting Plane Method

$$\mathcal{F}_{\text{IP}} := \{x \in \mathbb{Z}_+^n : Ax \leq b\}$$

$$\mathcal{F}_{\text{LP}} := \{x \in \mathbb{R}_+^n : Ax \leq b\}$$



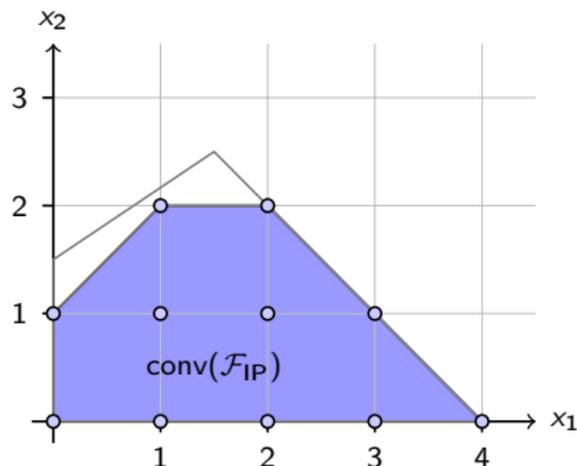
# General Cutting Plane Method

## Observation

- ▷  $\text{conv}(\mathcal{F}_{\text{IP}})$  is a polyhedron
- ▷ IP can be formulated as LP

## Problems with $\text{conv}(\mathcal{F}_{\text{IP}})$ :

- ▷ linear description not known
- ▷ large nr. of constraints needed



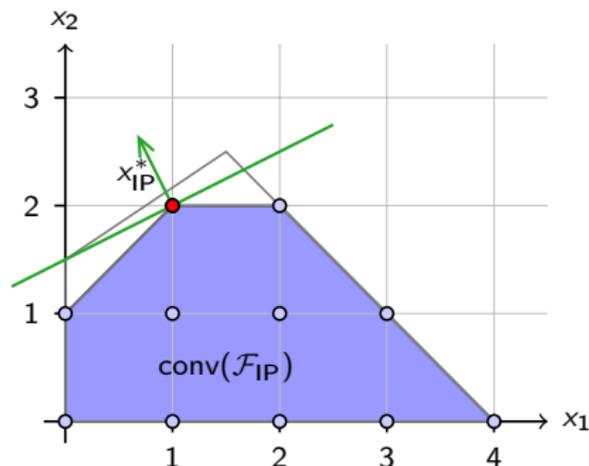
# General Cutting Plane Method

## Observation

- ▷  $\text{conv}(\mathcal{F}_{\text{IP}})$  is a polyhedron
- ▷ IP can be formulated as LP

## Problems with $\text{conv}(\mathcal{F}_{\text{IP}})$ :

- ▷ linear description not known
- ▷ large nr. of constraints needed



$$\min\{c^T x : x \in \text{conv}(\mathcal{F}_{\text{IP}})\}$$

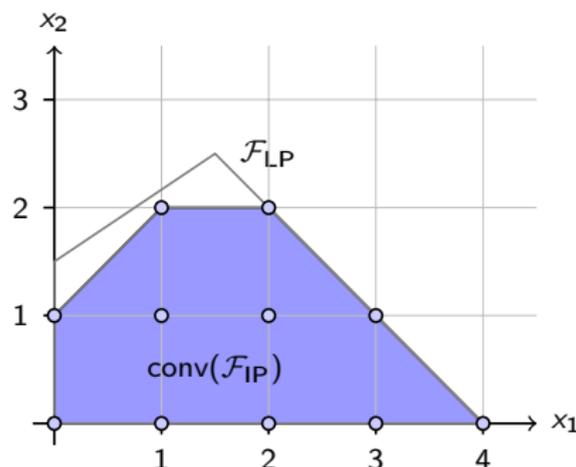
# General Cutting Plane Method

## Observation

- ▷  $\text{conv}(\mathcal{F}_{\text{IP}})$  is a polyhedron
- ▷ IP can be formulated as LP

## Problems with $\text{conv}(\mathcal{F}_{\text{IP}})$ :

- ▷ linear description not known
- ▷ large nr. of constraints needed



$$\min\{c^T x : x \in \text{conv}(\mathcal{F}_{\text{IP}})\}$$

$$\min\{c^T x : x \in \mathcal{F}_{\text{LP}}\} \leq \min\{c^T x : x \in \mathcal{F}\} = \min\{c^T x : x \in \text{conv}(\mathcal{F}_{\text{IP}})\}$$

# General Cutting Plane Method

## Algorithm

1.  $\mathcal{F} \leftarrow \mathcal{F}_{LP}$

2. Solve

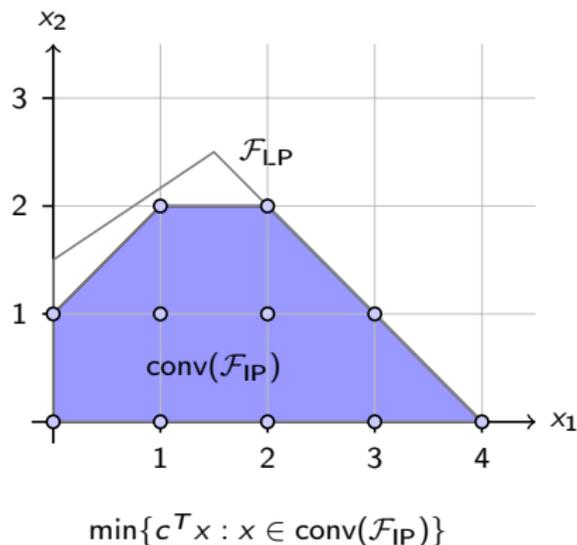
$$\begin{array}{ll} \min & c^T x \\ \text{s.t.} & x \in \mathcal{F} \end{array}$$

3. If  $x^* \in \mathcal{F}_{IP}$ : Stop

4. Add inequality to  $\mathcal{F}$  that is ...

- ▶ valid for  $\text{conv}(\mathcal{F}_{IP})$  but
- ▶ violated by  $x^*$ .

5. Goto 2.



# General Cutting Plane Method

## Algorithm

1.  $\mathcal{F} \leftarrow \mathcal{F}_{LP}$

2. Solve

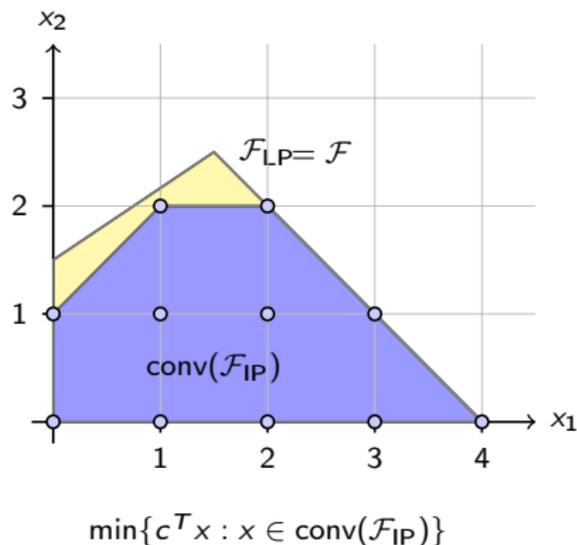
$$\begin{array}{ll} \min & c^T x \\ \text{s.t.} & x \in \mathcal{F} \end{array}$$

3. If  $x^* \in \mathcal{F}_{IP}$ : Stop

4. Add inequality to  $\mathcal{F}$  that is ...

- ▶ valid for  $\text{conv}(\mathcal{F}_{IP})$  but
- ▶ violated by  $x^*$ .

5. Goto 2.



# General Cutting Plane Method

## Algorithm

1.  $\mathcal{F} \leftarrow \mathcal{F}_{LP}$

2. Solve

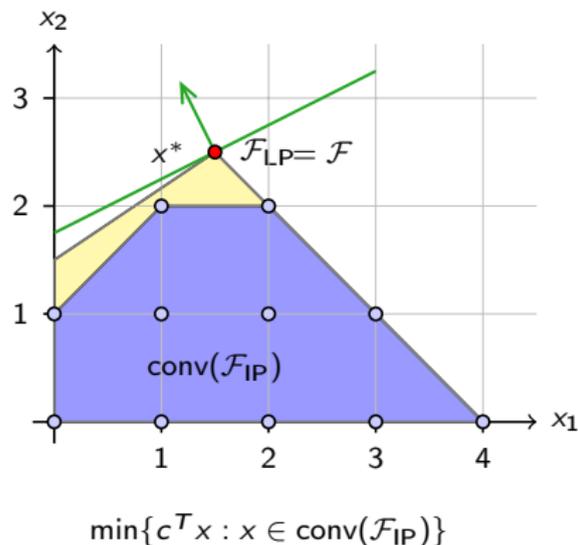
$$\begin{array}{ll} \min & c^T x \\ \text{s.t.} & x \in \mathcal{F} \end{array}$$

3. If  $x^* \in \mathcal{F}_{IP}$ : Stop

4. Add inequality to  $\mathcal{F}$  that is ...

- ▶ valid for  $\text{conv}(\mathcal{F}_{IP})$  but
- ▶ violated by  $x^*$ .

5. Goto 2.



# General Cutting Plane Method

## Algorithm

1.  $\mathcal{F} \leftarrow \mathcal{F}_{LP}$

2. Solve

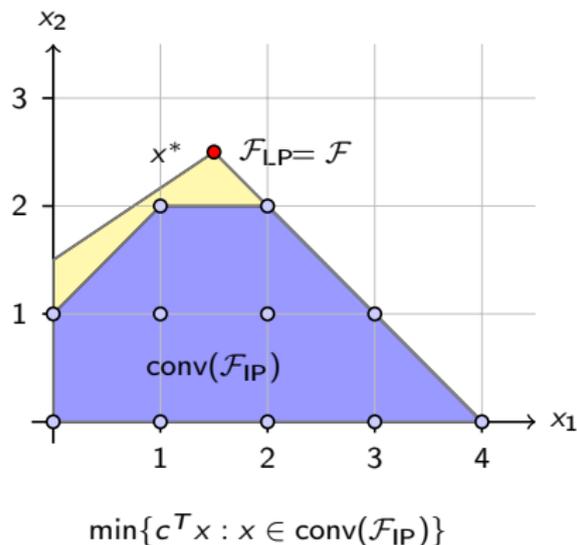
$$\begin{array}{ll} \min & c^T x \\ \text{s.t.} & x \in \mathcal{F} \end{array}$$

3. If  $x^* \in \mathcal{F}_{IP}$ : Stop

4. Add inequality to  $\mathcal{F}$  that is ...

- ▶ valid for  $\text{conv}(\mathcal{F}_{IP})$  but
- ▶ violated by  $x^*$ .

5. Goto 2.



# General Cutting Plane Method

## Algorithm

1.  $\mathcal{F} \leftarrow \mathcal{F}_{LP}$

2. Solve

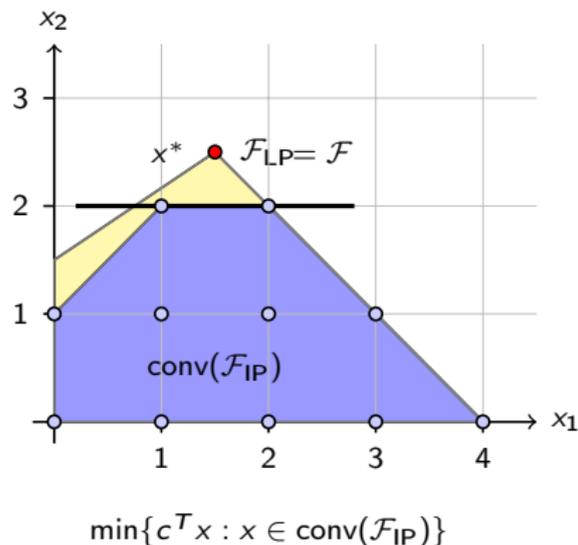
$$\begin{array}{ll} \min & c^T x \\ \text{s.t.} & x \in \mathcal{F} \end{array}$$

3. If  $x^* \in \mathcal{F}_{IP}$ : Stop

4. Add inequality to  $\mathcal{F}$  that is ...

- ▶ valid for  $\text{conv}(\mathcal{F}_{IP})$  but
- ▶ violated by  $x^*$ .

5. Goto 2.



# General Cutting Plane Method

## Algorithm

1.  $\mathcal{F} \leftarrow \mathcal{F}_{LP}$

2. Solve

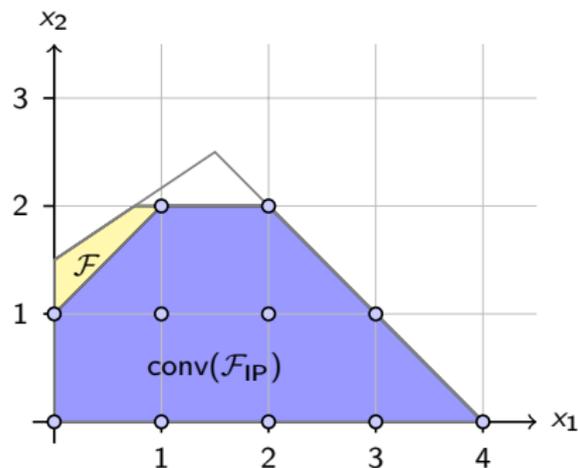
$$\begin{array}{ll} \min & c^T x \\ \text{s.t.} & x \in \mathcal{F} \end{array}$$

3. If  $x^* \in \mathcal{F}_{IP}$ : Stop

4. Add inequality to  $\mathcal{F}$  that is ...

- ▶ valid for  $\text{conv}(\mathcal{F}_{IP})$  but
- ▶ violated by  $x^*$ .

5. Goto 2.



$$\min\{c^T x : x \in \text{conv}(\mathcal{F}_{IP})\}$$

# General Cutting Plane Method

## Algorithm

1.  $\mathcal{F} \leftarrow \mathcal{F}_{LP}$

2. Solve

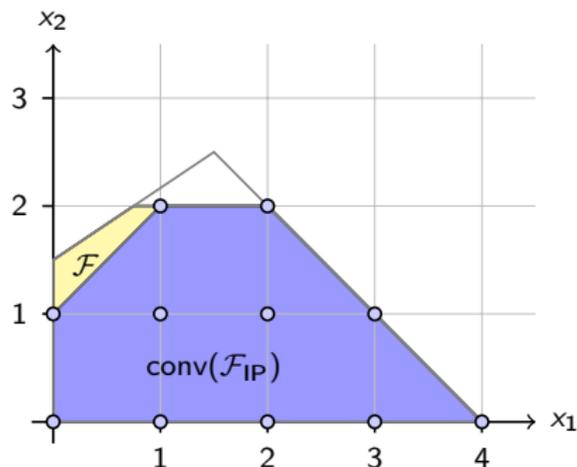
$$\begin{array}{ll} \min & c^T x \\ \text{s.t.} & x \in \mathcal{F} \end{array}$$

3. If  $x^* \in \mathcal{F}_{IP}$ : Stop

4. Add inequality to  $\mathcal{F}$  that is ...

- ▶ valid for  $\text{conv}(\mathcal{F}_{IP})$  but
- ▶ violated by  $x^*$ .

5. Goto 2.



$$\min\{c^T x : x \in \text{conv}(\mathcal{F}_{IP})\}$$

# General Cutting Plane Method

## Algorithm

1.  $\mathcal{F} \leftarrow \mathcal{F}_{LP}$

2. Solve

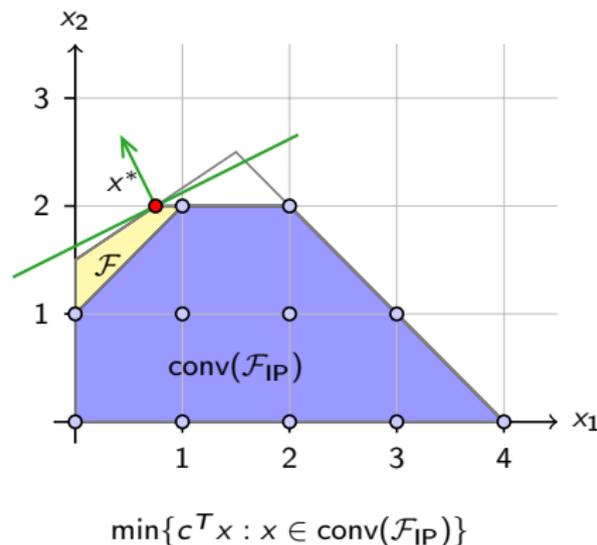
$$\begin{array}{ll} \min & c^T x \\ \text{s.t.} & x \in \mathcal{F} \end{array}$$

3. If  $x^* \in \mathcal{F}_{IP}$ : Stop

4. Add inequality to  $\mathcal{F}$  that is ...

- ▶ valid for  $\text{conv}(\mathcal{F}_{IP})$  but
- ▶ violated by  $x^*$ .

5. Goto 2.



# General Cutting Plane Method

## Algorithm

1.  $\mathcal{F} \leftarrow \mathcal{F}_{LP}$

2. Solve

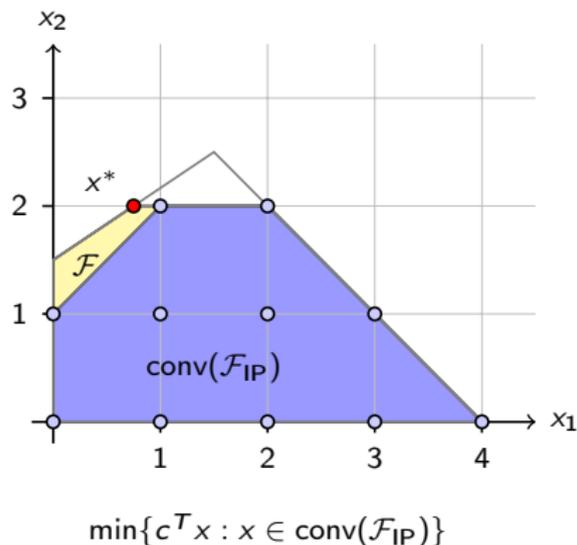
$$\begin{array}{ll} \min & c^T x \\ \text{s.t.} & x \in \mathcal{F} \end{array}$$

3. If  $x^* \in \mathcal{F}_{IP}$ : Stop

4. Add inequality to  $\mathcal{F}$  that is ...

- ▶ valid for  $\text{conv}(\mathcal{F}_{IP})$  but
- ▶ violated by  $x^*$ .

5. Goto 2.



# General Cutting Plane Method

## Algorithm

1.  $\mathcal{F} \leftarrow \mathcal{F}_{LP}$

2. Solve

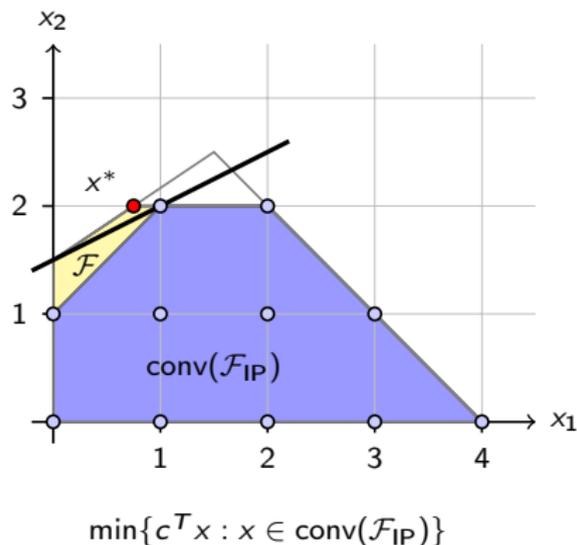
$$\begin{array}{ll} \min & c^T x \\ \text{s.t.} & x \in \mathcal{F} \end{array}$$

3. If  $x^* \in \mathcal{F}_{IP}$ : Stop

4. Add inequality to  $\mathcal{F}$  that is ...

- ▶ valid for  $\text{conv}(\mathcal{F}_{IP})$  but
- ▶ violated by  $x^*$ .

5. Goto 2.



# General Cutting Plane Method

## Algorithm

1.  $\mathcal{F} \leftarrow \mathcal{F}_{LP}$

2. Solve

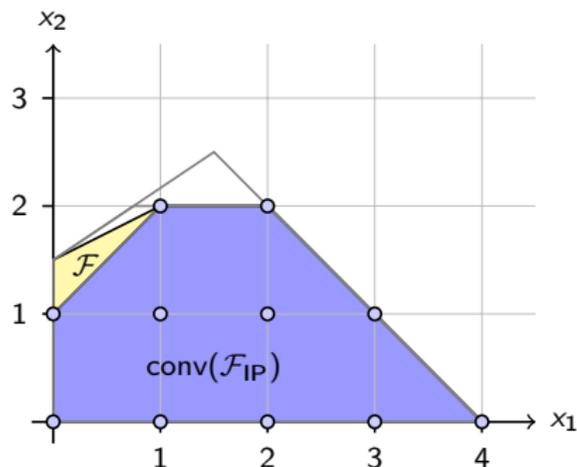
$$\begin{array}{ll} \min & c^T x \\ \text{s.t.} & x \in \mathcal{F} \end{array}$$

3. If  $x^* \in \mathcal{F}_{IP}$ : Stop

4. Add inequality to  $\mathcal{F}$  that is ...

- ▶ valid for  $\text{conv}(\mathcal{F}_{IP})$  but
- ▶ violated by  $x^*$ .

5. Goto 2.



# General Cutting Plane Method

## Algorithm

1.  $\mathcal{F} \leftarrow \mathcal{F}_{LP}$

2. Solve

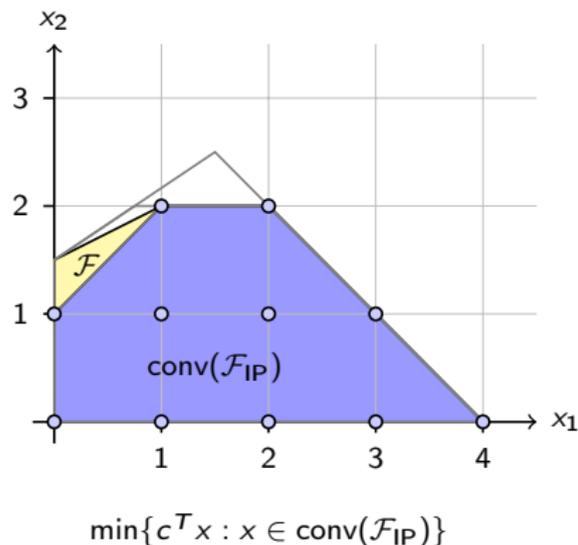
$$\begin{array}{ll} \min & c^T x \\ \text{s.t.} & x \in \mathcal{F} \end{array}$$

3. If  $x^* \in \mathcal{F}_{IP}$ : Stop

4. Add inequality to  $\mathcal{F}$  that is ...

- ▶ valid for  $\text{conv}(\mathcal{F}_{IP})$  but
- ▶ violated by  $x^*$ .

5. Goto 2.



# General Cutting Plane Method

## Algorithm

1.  $\mathcal{F} \leftarrow \mathcal{F}_{LP}$

2. Solve

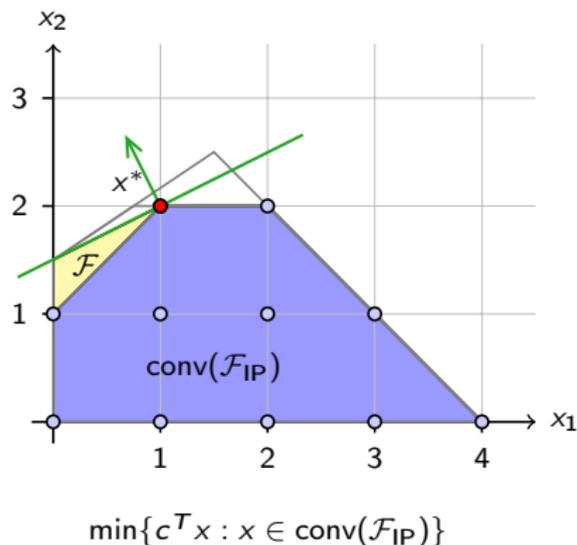
$$\begin{array}{ll} \min & c^T x \\ \text{s.t.} & x \in \mathcal{F} \end{array}$$

3. If  $x^* \in \mathcal{F}_{IP}$ : Stop

4. Add inequality to  $\mathcal{F}$  that is ...

- ▶ valid for  $\text{conv}(\mathcal{F}_{IP})$  but
- ▶ violated by  $x^*$ .

5. Goto 2.



# General Cutting Plane Method

## Algorithm

1.  $\mathcal{F} \leftarrow \mathcal{F}_{LP}$

2. Solve

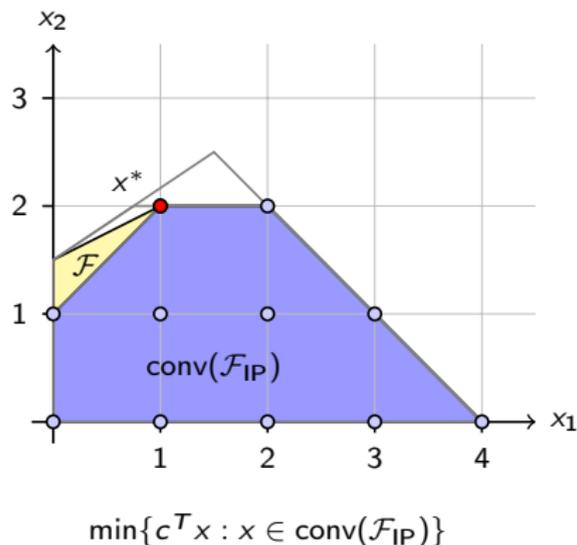
$$\begin{array}{ll} \min & c^T x \\ \text{s.t.} & x \in \mathcal{F} \end{array}$$

3. If  $x^* \in \mathcal{F}_{IP}$ : Stop

4. Add inequality to  $\mathcal{F}$  that is ...

- ▶ valid for  $\text{conv}(\mathcal{F}_{IP})$  but
- ▶ violated by  $x^*$ .

5. Goto 2.



# General Cutting Plane Method

## Algorithm

1.  $\mathcal{F} \leftarrow \mathcal{F}_{LP}$

2. Solve

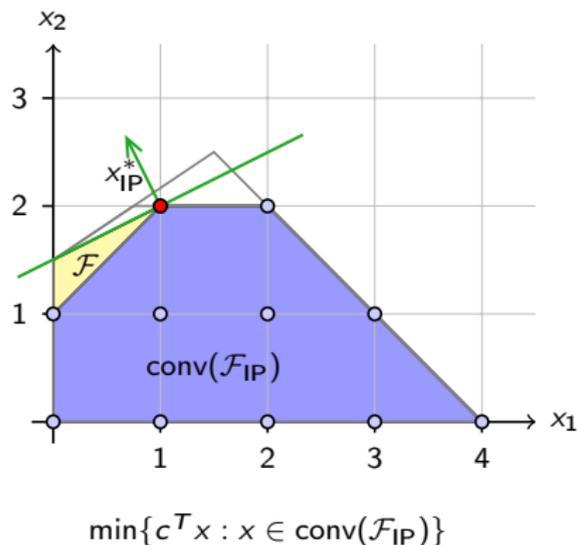
$$\begin{array}{ll} \min & c^T x \\ \text{s.t.} & x \in \mathcal{F} \end{array}$$

3. If  $x^* \in \mathcal{F}_{IP}$ : Stop

4. Add inequality to  $\mathcal{F}$  that is ...

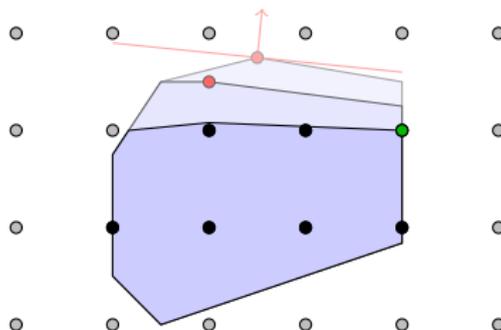
- ▶ valid for  $\text{conv}(\mathcal{F}_{IP})$  but
- ▶ violated by  $x^*$ .

5. Goto 2.



## Techniques

- ▷ **General cuts:**
  - ▶ complemented MIR cuts
  - ▶ Gomory mixed integer cuts
  - ▶ strong Chvátal-Gomory cuts
  - ▶  $\{0, \frac{1}{2}\}$ -cuts
  - ▶ implied bound cuts
- ▷ **Problem specific cuts:**
  - ▶ 0-1 knapsack problem
  - ▶ stable set problem
  - ▶ 0-1 single node flow problem
  - ▶ multi-commodity-flow problem

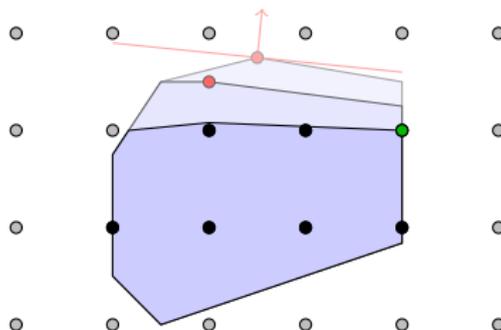


## Results

- ▷ Very **important** component
- ▷ In particular, **c-MIR cuts**
- ▷ **Coordination** important

## Techniques

- ▷ **General cuts:**
  - ▶ complemented MIR cuts
  - ▶ Gomory mixed integer cuts
  - ▶ strong Chvátal-Gomory cuts
  - ▶  $\{0, \frac{1}{2}\}$ -cuts
  - ▶ implied bound cuts
- ▷ **Problem specific cuts:**
  - ▶ **0-1 knapsack problem**
  - ▶ stable set problem
  - ▶ 0-1 single node flow problem
  - ▶ multi-commodity-flow problem



## Results

- ▷ Very **important** component
- ▷ In particular, **c-MIR cuts**
- ▷ **Coordination** important

# Cuts for the 0-1 Knapsack Problem

Feasible region:  $(b \in \mathbb{Z}_+, a_j \in \mathbb{Z}_+ \quad \forall j \in N)$

$$X^{BK} := \{ x \in \{0,1\}^n : \sum_{j \in N} a_j x_j \leq b \}$$

Minimal Cover:  $C \subseteq N$

- ▷  $\sum_{j \in C} a_j > b$
- ▷  $\sum_{j \in C \setminus \{i\}} a_j \leq b \quad \forall i \in C$

Minimal Cover Inequality

$$\sum_{j \in C} x_j \leq |C| - 1$$

$$5x_1 + 6x_2 + 2x_3 + 2x_4 \leq 8$$

Minimal cover:

$$C = \{2, 3, 4\}$$

Minimal cover inequality:

$$x_2 + x_3 + x_4 \leq 2$$

Theorem:

If  $C \subseteq N$  is a **minimal cover** for  $X^{BK}$ , then the **minimal cover inequality**

$$\sum_{j \in C} x_j \leq |C| - 1$$

defines a facet of

$$\text{conv}( X^{BK} \cap \{x \in \{0, 1\}^n : x_j = 0 \text{ for all } j \in N \setminus C \} ).$$

Use **sequential up-lifting** to strengthen minimal cover inequalities.

▷  $X^{BK} = \{x \in \{0, 1\}^4 : 5x_1 + 6x_2 + 2x_3 + 2x_4 \leq 8\}$

▷  $C = \{2, 3, 4\}$

$$\sum_{j \in C} x_j \leq 2 \quad \text{valid for } X^{BK} \cap \{x \in \{0, 1\}^4 : x_1 = 0\}$$

(I)  $\sum_{j \in C} x_j + \alpha_1 x_1 \leq 2 \quad \text{valid for } X^{BK}$

$$\triangleright X^{BK} = \{x \in \{0, 1\}^4 : 5x_1 + 6x_2 + 2x_3 + 2x_4 \leq 8\}$$

$$\triangleright C = \{2, 3, 4\}$$

$$\sum_{j \in C} x_j \leq 2 \quad \text{valid for } X^{BK} \cap \{x \in \{0, 1\}^4 : x_1 = 0\}$$
$$(I) \quad \sum_{j \in C} x_j + \alpha_1 x_1 \leq 2 \quad \text{valid for } X^{BK}$$

**Step 1:** Inequality (I) is valid for  $X^{BK} \cap \{x \in \{0, 1\}^4 : x_1 = 0\}$

$$\triangleright X^{BK} = \{x \in \{0, 1\}^4 : 5x_1 + 6x_2 + 2x_3 + 2x_4 \leq 8\}$$

$$\triangleright C = \{2, 3, 4\}$$

$$\begin{aligned} \sum_{j \in C} x_j &\leq 2 && \text{valid for } X^{BK} \cap \{x \in \{0, 1\}^4 : x_1 = 0\} \\ (I) \quad \sum_{j \in C} x_j + \alpha_1 x_1 &\leq 2 && \text{valid for } X^{BK} \end{aligned}$$

**Step 1:** Inequality (I) is valid for  $X^{BK} \cap \{x \in \{0, 1\}^4 : x_1 = 0\}$

$$\Leftrightarrow \sum_{j \in C} x_j + \alpha_1 \cdot 0 \leq 2 \text{ is valid for } X^{BK} \cap \{x \in \{0, 1\}^4 : x_1 = 0\}$$

$$\triangleright X^{BK} = \{x \in \{0, 1\}^4 : 5x_1 + 6x_2 + 2x_3 + 2x_4 \leq 8\}$$

$$\triangleright C = \{2, 3, 4\}$$

$$\sum_{j \in C} x_j \leq 2 \quad \text{valid for } X^{BK} \cap \{x \in \{0, 1\}^4 : x_1 = 0\}$$
$$(I) \quad \sum_{j \in C} x_j + \alpha_1 x_1 \leq 2 \quad \text{valid for } X^{BK}$$

**Step 1:** Inequality (I) is valid for  $X^{BK} \cap \{x \in \{0, 1\}^4 : x_1 = 0\}$

$$\Leftrightarrow \sum_{j \in C} x_j + \alpha_1 \cdot 0 \leq 2 \text{ is valid for } X^{BK} \cap \{x \in \{0, 1\}^4 : x_1 = 0\}$$

$$\Leftrightarrow \alpha_1 \in [-\infty, \infty]$$

$$\triangleright X^{BK} = \{x \in \{0, 1\}^4 : 5x_1 + 6x_2 + 2x_3 + 2x_4 \leq 8\}$$

$$\triangleright C = \{2, 3, 4\}$$

$$\sum_{j \in C} x_j \leq 2 \quad \text{valid for } X^{BK} \cap \{x \in \{0, 1\}^4 : x_1 = 0\}$$
$$(I) \quad \sum_{j \in C} x_j + \alpha_1 x_1 \leq 2 \quad \text{valid for } X^{BK}$$

**Step 2:** Inequality (I) is valid for  $X^{BK} \cap \{x \in \{0, 1\}^4 : x_1 = 1\}$

$$\triangleright X^{BK} = \{x \in \{0, 1\}^4 : 5x_1 + 6x_2 + 2x_3 + 2x_4 \leq 8\}$$

$$\triangleright C = \{2, 3, 4\}$$

$$\begin{aligned} \sum_{j \in C} x_j &\leq 2 && \text{valid for } X^{BK} \cap \{x \in \{0, 1\}^4 : x_1 = 0\} \\ (I) \quad \sum_{j \in C} x_j + \alpha_1 x_1 &\leq 2 && \text{valid for } X^{BK} \end{aligned}$$

**Step 2:** Inequality (I) is valid for  $X^{BK} \cap \{x \in \{0, 1\}^4 : x_1 = 1\}$

$$\Leftrightarrow \sum_{j \in C} x_j + \alpha_1 \cdot 1 \leq 2 \text{ is valid for } \{x \in \{0, 1\}^4 : 6x_2 + 2x_3 + 2x_4 \leq 8 - 5\}$$

$$\triangleright X^{BK} = \{x \in \{0, 1\}^4 : 5x_1 + 6x_2 + 2x_3 + 2x_4 \leq 8\}$$

$$\triangleright C = \{2, 3, 4\}$$

$$\sum_{j \in C} x_j \leq 2 \quad \text{valid for } X^{BK} \cap \{x \in \{0, 1\}^4 : x_1 = 0\}$$
$$(I) \quad \sum_{j \in C} x_j + \alpha_1 x_1 \leq 2 \quad \text{valid for } X^{BK}$$

**Step 2:** Inequality (I) is valid for  $X^{BK} \cap \{x \in \{0, 1\}^4 : x_1 = 1\}$

$$\Leftrightarrow \sum_{j \in C} x_j + \alpha_1 \cdot 1 \leq 2 \text{ is valid for } \{x \in \{0, 1\}^4 : 6x_2 + 2x_3 + 2x_4 \leq 8 - 5\}$$

$$\Leftrightarrow \max \left\{ \sum_{j \in C} x_j : 6x_2 + 2x_3 + 2x_4 \leq 3, x \in \{0, 1\}^4 \right\} + \alpha_1 \cdot 1 \leq 2$$

$$\triangleright X^{BK} = \{x \in \{0, 1\}^4 : 5x_1 + 6x_2 + 2x_3 + 2x_4 \leq 8\}$$

$$\triangleright C = \{2, 3, 4\}$$

$$\sum_{j \in C} x_j \leq 2 \quad \text{valid for } X^{BK} \cap \{x \in \{0, 1\}^4 : x_1 = 0\}$$
$$(I) \quad \sum_{j \in C} x_j + \alpha_1 x_1 \leq 2 \quad \text{valid for } X^{BK}$$

**Step 2:** Inequality (I) is valid for  $X^{BK} \cap \{x \in \{0, 1\}^4 : x_1 = 1\}$

$$\Leftrightarrow \sum_{j \in C} x_j + \alpha_1 \cdot 1 \leq 2 \text{ is valid for } \{x \in \{0, 1\}^4 : 6x_2 + 2x_3 + 2x_4 \leq 8 - 5\}$$

$$\Leftrightarrow \max \left\{ \sum_{j \in C} x_j : 6x_2 + 2x_3 + 2x_4 \leq 3, x \in \{0, 1\}^4 \right\} + \alpha_1 \cdot 1 \leq 2$$

$$\Leftrightarrow 1 + \alpha_1 \leq 2 \Leftrightarrow \alpha_1 \leq 1$$

$$\triangleright X^{BK} = \{x \in \{0, 1\}^4 : 5x_1 + 6x_2 + 2x_3 + 2x_4 \leq 8\}$$

$$\triangleright C = \{2, 3, 4\}$$

$$\begin{array}{ll} \sum_{j \in C} x_j & \leq 2 \quad \text{valid for } X^{BK} \cap \{x \in \{0, 1\}^4 : x_1 = 0\} \\ (I) \quad \sum_{j \in C} x_j + \alpha_1 x_1 & \leq 2 \quad \text{valid for } X^{BK} \end{array}$$

**Step 1:** Inequ. (I) valid for  $X^{BK} \cap \{x \in \{0, 1\}^4 : x_1 = 0\}$  for all  $\alpha_1 \in [-\infty, \infty]$

**Step 2:** Inequ. (I) valid for  $X^{BK} \cap \{x \in \{0, 1\}^4 : x_1 = 1\}$  for all  $\alpha_1 \leq 1$

**Result:** Inequ. (I) valid for  $X^{BK}$  for all  $\alpha_1 \leq 1$

# Sequential Up-lifting

- ▷  $(j_1, \dots, j_t)$  lifting sequence of the variables in  $N \setminus C$
- ▷  $X^i := X^{BK} \cap \{x \in \{0, 1\}^n : x_{j_{i+1}} = \dots = x_{j_t} = 0\}$

$$\sum_{j \in C} x_j \leq |C| - 1 \quad \text{valid for } X^0$$

$$\sum_{j \in C} x_j + \alpha_{j_1} x_{j_1} \leq |C| - 1 \quad \text{valid for } X^1$$

⋮

$$\sum_{j \in C} x_j + \sum_{k=1}^t \alpha_{j_k} x_{j_k} \leq |C| - 1 \quad \text{valid for } X^t = X^{BK}$$

# Sequential Up-lifting

- ▷  $(j_1, \dots, j_t)$  lifting sequence of the variables in  $N \setminus C$
- ▷  $X^i := X^{BK} \cap \{x \in \{0, 1\}^n : x_{j_{i+1}} = \dots = x_{j_t} = 0\}$

$$\sum_{j \in C} x_j \leq |C| - 1 \quad \text{valid for } X^0$$

$$\sum_{j \in C} x_j + \alpha_{j_1} x_{j_1} \leq |C| - 1 \quad \text{valid for } X^1$$

⋮

$$\sum_{j \in C} x_j + \sum_{k=1}^t \alpha_{j_k} x_{j_k} \leq |C| - 1 \quad \text{valid for } X^t = X^{BK}$$

- ▷ Different lifting sequences may lead to different inequalities!
- ▷ Use sequential **up- and down-lifting**!

# Sequential Up- and Down-lifting

## Theorem:

If  $C \subseteq N$  is a **minimal cover** for  $X^{BK}$  and  $(C_1, C_2)$  is any partition of  $C$  with  $C_1 \neq \emptyset$ , then inequality

$$\sum_{j \in C_1} x_j \leq |C_1| - 1$$

defines a **facet** of

$$\text{conv}( X^{BK} \cap \{x \in \{0, 1\}^n : x_j = 0 \text{ for all } j \in N \setminus C, \\ x_j = 1 \text{ for all } j \in C_2 \} ).$$

- ▷ **Up-lifting**: variables in  $N \setminus C$
- ▷ **Down-lifting**: variables in  $C_2$

# Outline of the Separation Algorithm

## Step 1 (Initial cover)

- ▷ Determine an initial cover  $C$  for  $X^{BK}$

## Step 2 (Minimal cover and partition)

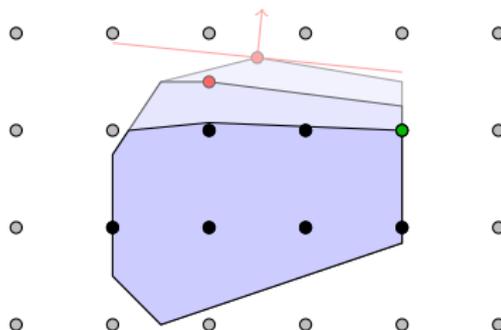
- ▷ Make the initial cover minimal by removing vars from  $C$
- ▷ Find a partition  $(C_1, C_2)$  of  $C$  with  $C_1 \neq \emptyset$

## Step 3 (Lifting)

- ▷ Determine a lifting sequence of the variables in  $N \setminus C_1$
- ▷ Lift the inequality  $\sum_{j \in C_1} x_j \leq |C_1| - 1$  using sequential up- and down-lifting

## Techniques

- ▷ **General cuts:**
  - ▶ complemented MIR cuts
  - ▶ Gomory mixed integer cuts
  - ▶ strong Chvátal-Gomory cuts
  - ▶  $\{0, \frac{1}{2}\}$ -cuts
  - ▶ implied bound cuts
- ▷ **Problem specific cuts:**
  - ▶ 0-1 knapsack problem
  - ▶ **stable set problem**
  - ▶ 0-1 single node flow problem
  - ▶ multi-commodity-flow problem



## Results

- ▷ Very **important** component
- ▷ In particular, **c-MIR cuts**
- ▷ **Coordination** important

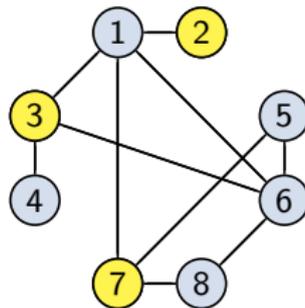
# Cuts for the Stable Set Problem

Stable set polytope for graph  $G = (V, E)$ :

$$\text{conv}(\{x \in \{0, 1\}^{|V|} : x_u + x_v \leq 1 \text{ for all } (u, v) \in E\})$$

Stable Set:  $S \subseteq V$

▷  $\forall u, v \in S : (u, v) \notin E$



Stable set

# Cuts for the Stable Set Problem

Stable set polytope for graph  $G = (V, E)$ :

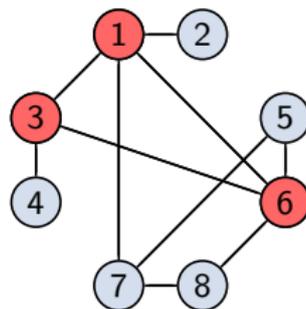
$$\text{conv}(\{x \in \{0, 1\}^{|V|} : x_u + x_v \leq 1 \text{ for all } (u, v) \in E\})$$

Stable Set:  $S \subseteq V$

$$\triangleright \forall u, v \in S : (u, v) \notin E$$

Clique:  $C \subseteq V$

$$\triangleright \forall u, v \in C : (u, v) \in E$$



Clique

# Cuts for the Stable Set Problem

Stable set polytope for graph  $G = (V, E)$ :

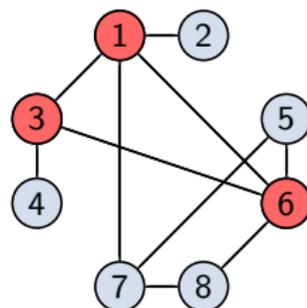
$$\text{conv}(\{x \in \{0, 1\}^{|V|} : x_u + x_v \leq 1 \text{ for all } (u, v) \in E\})$$

Stable Set:  $S \subseteq V$

$$\triangleright \forall u, v \in S : (u, v) \notin E$$

Clique:  $C \subseteq V$

$$\triangleright \forall u, v \in C : (u, v) \in E$$



$$x_1 + x_3 + x_6 \leq 1$$

→ Clique inequality:  $\sum_{j \in C} x_j \leq 1$  is valid for stable set polytope.

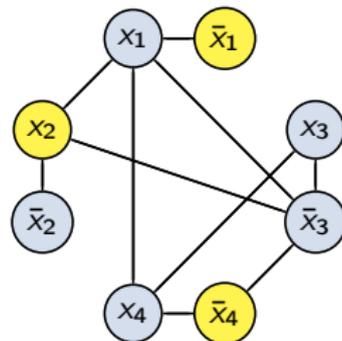
# Stable Set Relaxation of a MIP

Conflict Graph:  $G = (V, E)$

$V$ : node for every **binary variable**  $x_j$  and for its **complement**  $\bar{x}_j := 1 - x_j$

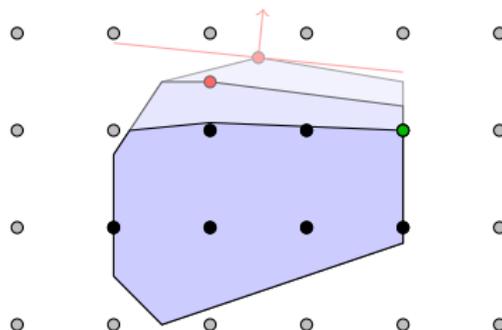
$E$ :  $(x_i, x_j) \in E \Leftrightarrow$  In any feasible MIP solution,  
 **$x_i$  and  $x_j$  cannot be one** at the same time

- Feasible MIP solution corresponds to stable set in conflict graph
- Stable set polytope on conflict graph is relaxation of MIP's feasible region



## Techniques

- ▷ General cuts:
  - ▶ complemented MIR cuts
  - ▶ Gomory mixed integer cuts
  - ▶ strong Chvátal-Gomory cuts
  - ▶  $\{0, \frac{1}{2}\}$ -cuts
  - ▶ implied bound cuts
- ▷ Problem specific cuts:
  - ▶ 0-1 knapsack problem
  - ▶ stable set problem
  - ▶ 0-1 single node flow problem
  - ▶ multi-commodity-flow problem



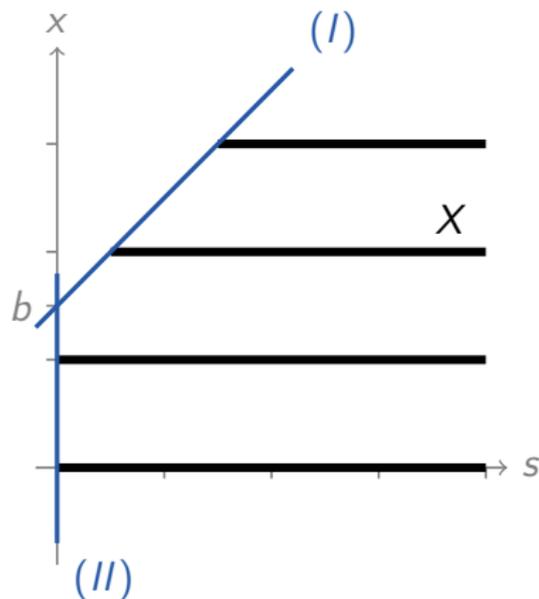
## Results

- ▷ Very important component
- ▷ In particular, c-MIR cuts
- ▷ Coordination important

# Mixed Integer Rounding (MIR) Cut

Elementary mixed integer set:

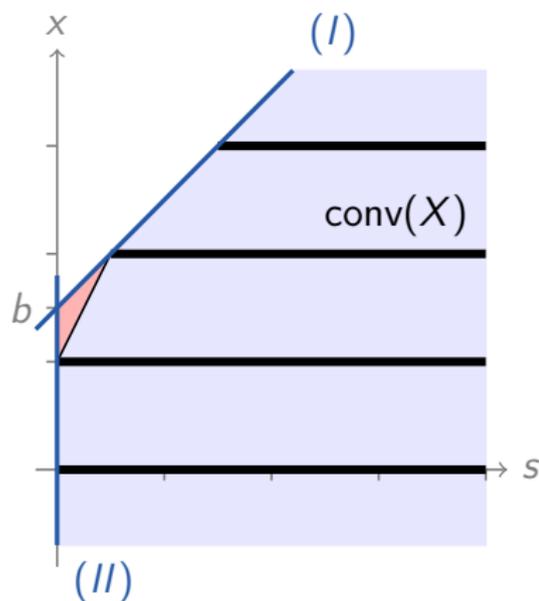
$$X := \{ (x, s) \in \mathbb{Z} \times \mathbb{R} : \begin{array}{ll} x \leq b + s & (I) \\ s \geq 0 & (II) \end{array} \}$$



# Mixed Integer Rounding (MIR) Cut

Elementary mixed integer set:

$$X := \{ (x, s) \in \mathbb{Z} \times \mathbb{R} : \begin{array}{ll} x \leq b + s & (I) \\ s \geq 0 & (II) \end{array} \}$$

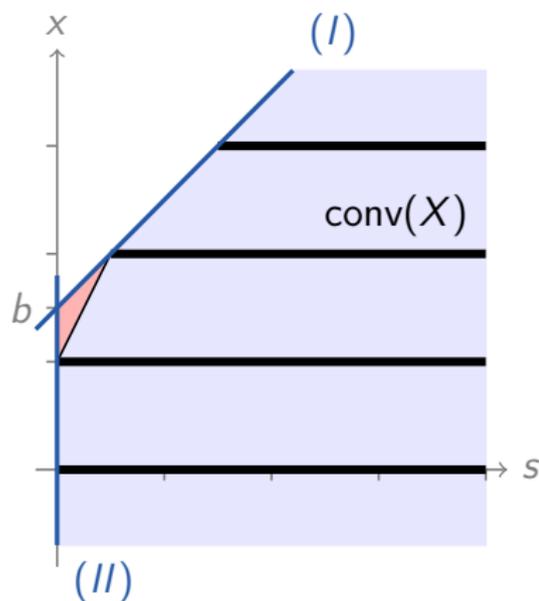


Inequalities (I) and (II) do not suffice to describe  $\text{conv}(X)$ .

# Mixed Integer Rounding (MIR) Cut

## Disjunctive argument:

- ▷ If an inequality is valid for  $X^1$  and for  $X^2$  it is also valid for  $X^1 \cup X^2$ .



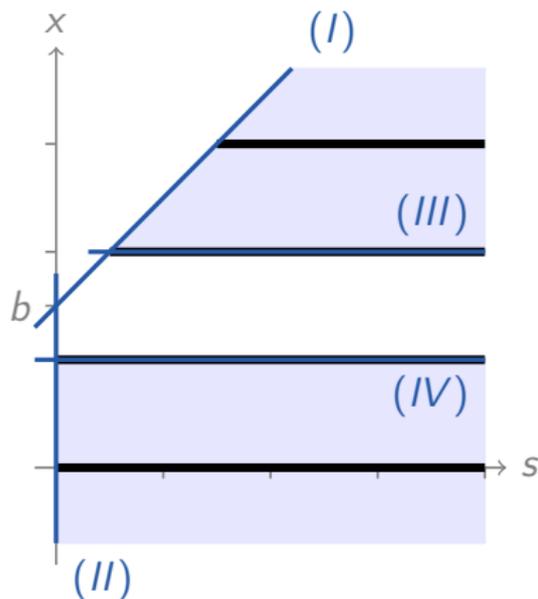
# Mixed Integer Rounding (MIR) Cut

## Disjunctive argument:

- ▷ If an inequality is valid for  $X^1$  and for  $X^2$  it is also valid for  $X^1 \cup X^2$ .

## Here:

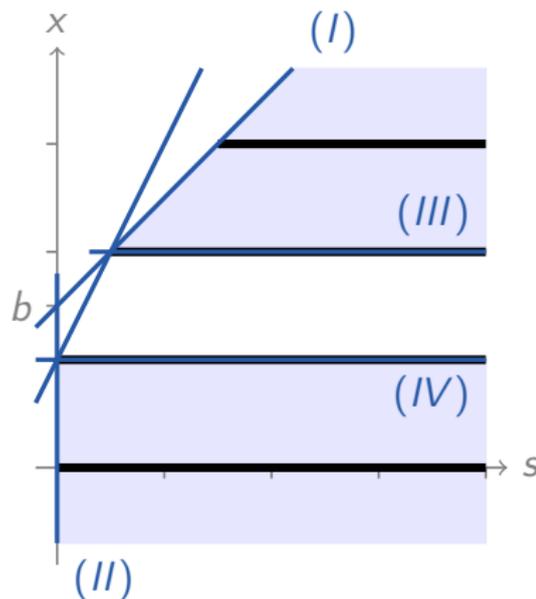
- ▷  $X^1$ : Add  $x \geq \lceil b \rceil$  (III)
- ▷  $X^2$ : Add  $x \leq \lfloor b \rfloor$  (IV)



# Mixed Integer Rounding (MIR) Cut

Inequality valid for  $X^1$  and for  $X^2$ :

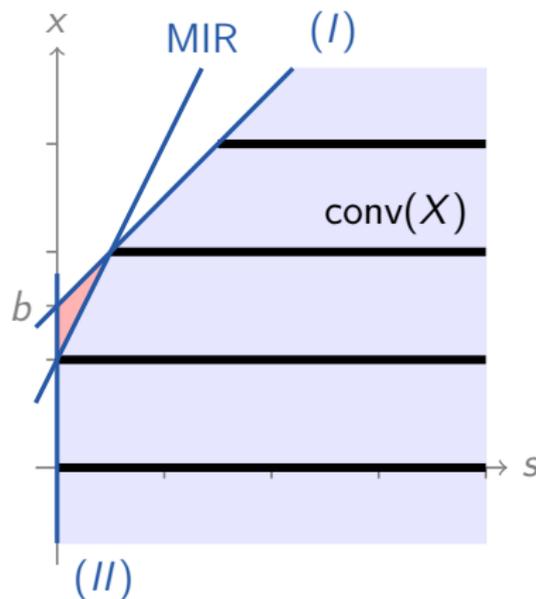
$$x \leq \underbrace{\lfloor b \rfloor + \frac{s}{1-f_b}}_{(I)+f_b(III) \text{ and } (II)+(1-f_b)(IV)}$$



# Mixed Integer Rounding (MIR) Cut

Inequality valid for  $X^1 \cup X^2 = X$ :

$$\underbrace{x \leq \lfloor b \rfloor + \frac{s}{1 - f_b}}_{\text{MIR inequality}}$$



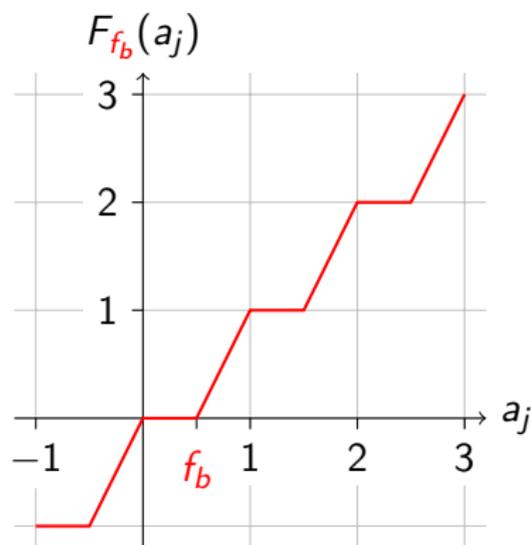
Mixed knapsack set:

$$\left\{ (x, s) \in \mathbb{Z}_+^n \times \mathbb{R}_+ : \right.$$
$$\sum_{j \in N} a_j x_j \leq b + s$$
$$\left. x_j \leq u_j \quad j \in N \right\}$$

# Complemented MIR (C-MIR) Cut

MIR inequality:

$$\sum_{j \in N} F_{f_b}(a_j) x_j \leq \lfloor b \rfloor + \frac{s}{1 - f_b}$$

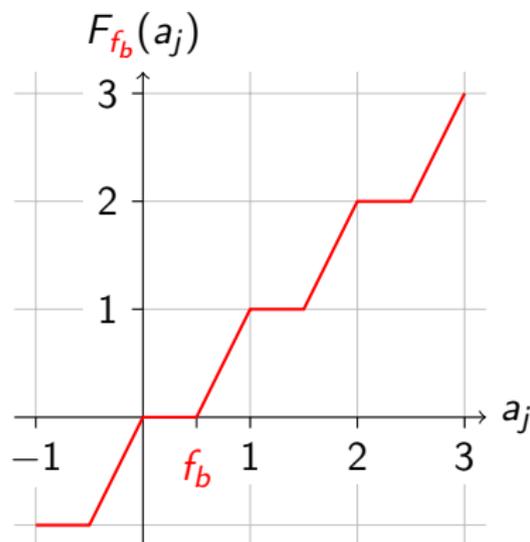


MIR inequality:

$$\sum_{j \in N} F_{f_b}(a_j) x_j \leq \lfloor b \rfloor + \frac{s}{1 - f_b}$$

C-MIR inequality:

- ▷ Divide by  $\delta \in \mathbb{Q}_+ \setminus \{0\}$
- ▷ Complement some integer vars ( $x_j = u_j - \bar{x}_j$ )
- ▷ MIR inequality



# Example

$$\sum_{j \in N} a_j x_j \leq b + s$$

$\rightsquigarrow$

$$\sum_{j \in N} F_{f_b}(a_j) x_j \leq \lfloor b \rfloor + \frac{s}{1 - f_b}$$

# Example

$$\sum_{j \in N} a_j x_j \leq b + s$$

$\rightsquigarrow$

$$\sum_{j \in N} F_{f_b}(a_j) x_j \leq \lfloor b \rfloor + \frac{s}{1 - f_b}$$

$$1x_1 + 4x_2 \leq \frac{11}{2} + s$$

Bounds:  $x_1, x_2 \leq 2$

# Example

$$\sum_{j \in N} a_j x_j \leq b + s$$

$\rightsquigarrow$

$$\sum_{j \in N} F_{f_b}(a_j) x_j \leq \lfloor b \rfloor + \frac{s}{1 - f_b}$$

$$1x_1 + 4x_2 \leq \frac{11}{2} + s$$

$$\text{Bounds: } x_1, x_2 \leq 2$$

For  $\delta = 1$ :

# Example

$$\sum_{j \in N} a_j x_j \leq b + s$$

$\rightsquigarrow$

$$\sum_{j \in N} F_{f_b}(a_j) x_j \leq \lfloor b \rfloor + \frac{s}{1 - f_b}$$

$$1x_1 + 4x_2 \leq \frac{11}{2} + s$$

Bounds:  $x_1, x_2 \leq 2$

For  $\delta = 1$ :

$$\triangleright f_{\frac{11}{2}} = \frac{11}{2} - \lfloor \frac{11}{2} \rfloor = \frac{1}{2}$$

# Example

$$\sum_{j \in N} a_j x_j \leq b + s$$

$\rightsquigarrow$

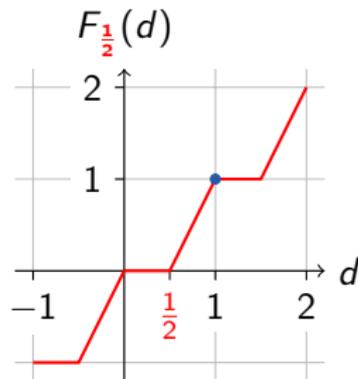
$$\sum_{j \in N} F_{f_b}(a_j) x_j \leq \lfloor b \rfloor + \frac{s}{1 - f_b}$$

$$1x_1 + 4x_2 \leq \frac{11}{2} + s$$

$$\text{Bounds: } x_1, x_2 \leq 2$$

For  $\delta = 1$ :

$$\triangleright f_{\frac{11}{2}} = \frac{11}{2} - \lfloor \frac{11}{2} \rfloor = \frac{1}{2}$$



# Example

$$\sum_{j \in N} a_j x_j \leq b + s$$

$\rightsquigarrow$

$$\sum_{j \in N} F_{f_b}(a_j) x_j \leq \lfloor b \rfloor + \frac{s}{1 - f_b}$$

$$1x_1 + 4x_2 \leq \frac{11}{2} + s$$

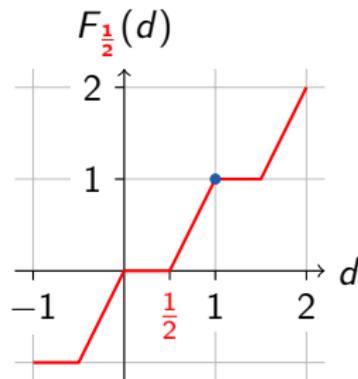
$$\text{Bounds: } x_1, x_2 \leq 2$$

$\rightsquigarrow$

$$1x_1 + 4x_2 \leq 5 + 2s$$

For  $\delta = 1$ :

$$\triangleright f_{\frac{11}{2}} = \frac{11}{2} - \lfloor \frac{11}{2} \rfloor = \frac{1}{2}$$



# Example

$$\sum_{j \in N} a_j x_j \leq b + s$$

$\rightsquigarrow$

$$\sum_{j \in N} F_{f_b}(a_j) x_j \leq \lfloor b \rfloor + \frac{s}{1 - f_b}$$

$$1x_1 + 4x_2 \leq \frac{11}{2} + s$$

$\rightsquigarrow$

$$1x_1 + 4x_2 \leq 5 + 2s$$

Bounds:  $x_1, x_2 \leq 2$

For  $\delta = 4$ ,  $x_1 = 2 - \bar{x}_1$ :

# Example

$$\sum_{j \in N} a_j x_j \leq b + s$$

$\rightsquigarrow$

$$\sum_{j \in N} F_{f_b}(a_j) x_j \leq \lfloor b \rfloor + \frac{s}{1 - f_b}$$

$$1x_1 + 4x_2 \leq \frac{11}{2} + s$$

$\rightsquigarrow$

$$1x_1 + 4x_2 \leq 5 + 2s$$

Bounds:  $x_1, x_2 \leq 2$

For  $\delta = 4$ ,  $x_1 = 2 - \bar{x}_1$ :

$$\triangleright -\frac{1}{4} \bar{x}_1 + x_2 \leq \frac{7}{8} + \frac{1}{4} s$$

# Example

$$\sum_{j \in N} a_j x_j \leq b + s$$

$\rightsquigarrow$

$$\sum_{j \in N} F_{f_b}(a_j) x_j \leq \lfloor b \rfloor + \frac{s}{1 - f_b}$$

$$1x_1 + 4x_2 \leq \frac{11}{2} + s$$

$\rightsquigarrow$

$$1x_1 + 4x_2 \leq 5 + 2s$$

Bounds:  $x_1, x_2 \leq 2$

For  $\delta = 4$ ,  $x_1 = 2 - \bar{x}_1$ :

$$\triangleright -\frac{1}{4} \bar{x}_1 + x_2 \leq \frac{7}{8} + \frac{1}{4} s$$

$$\triangleright f_{\frac{7}{8}} = \frac{7}{8} - \left\lfloor \frac{7}{8} \right\rfloor = \frac{7}{8}$$

# Example

$$\sum_{j \in N} a_j x_j \leq b + s$$

$\rightsquigarrow$

$$\sum_{j \in N} F_{f_b}(a_j) x_j \leq \lfloor b \rfloor + \frac{s}{1 - f_b}$$

$$1x_1 + 4x_2 \leq \frac{11}{2} + s$$

$\rightsquigarrow$

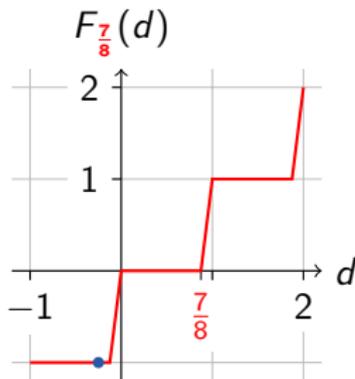
$$1x_1 + 4x_2 \leq 5 + 2s$$

Bounds:  $x_1, x_2 \leq 2$

For  $\delta = 4$ ,  $x_1 = 2 - \bar{x}_1$ :

$$\triangleright -\frac{1}{4} \bar{x}_1 + x_2 \leq \frac{7}{8} + \frac{1}{4} s$$

$$\triangleright f_{\frac{7}{8}} = \frac{7}{8} - \lfloor \frac{7}{8} \rfloor = \frac{7}{8}$$



# Example

$$\sum_{j \in N} a_j x_j \leq b + s$$

$\rightsquigarrow$

$$\sum_{j \in N} F_{f_b}(a_j) x_j \leq \lfloor b \rfloor + \frac{s}{1 - f_b}$$

$$1x_1 + 4x_2 \leq \frac{11}{2} + s$$

$\rightsquigarrow$

$$1x_1 + 4x_2 \leq 5 + 2s$$

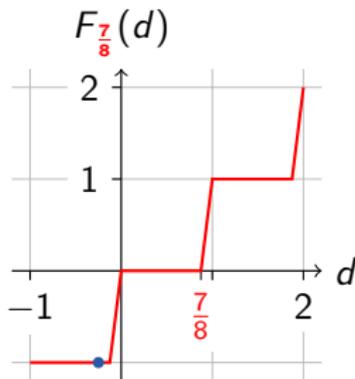
$$\text{Bounds: } x_1, x_2 \leq 2$$

$$-1\bar{x}_1 + 1x_2 \leq 0 + 2s$$

For  $\delta = 4$ ,  $x_1 = 2 - \bar{x}_1$ :

$$\triangleright -\frac{1}{4}\bar{x}_1 + x_2 \leq \frac{7}{8} + \frac{1}{4}s$$

$$\triangleright f_{\frac{7}{8}} = \frac{7}{8} - \lfloor \frac{7}{8} \rfloor = \frac{7}{8}$$



# Example

$$\sum_{j \in N} a_j x_j \leq b + s$$

$\rightsquigarrow$

$$\sum_{j \in N} F_{f_b}(a_j) x_j \leq \lfloor b \rfloor + \frac{s}{1 - f_b}$$

$$1x_1 + 4x_2 \leq \frac{11}{2} + s$$

$\rightsquigarrow$

$$1x_1 + 4x_2 \leq 5 + 2s$$

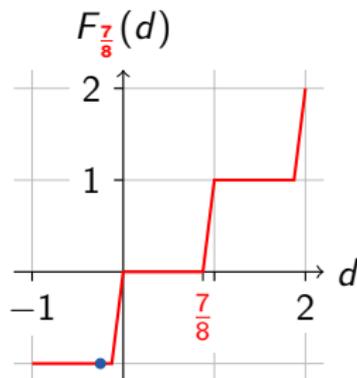
$$\text{Bounds: } x_1, x_2 \leq 2$$

$$1x_1 + 1x_2 \leq 2 + 2s$$

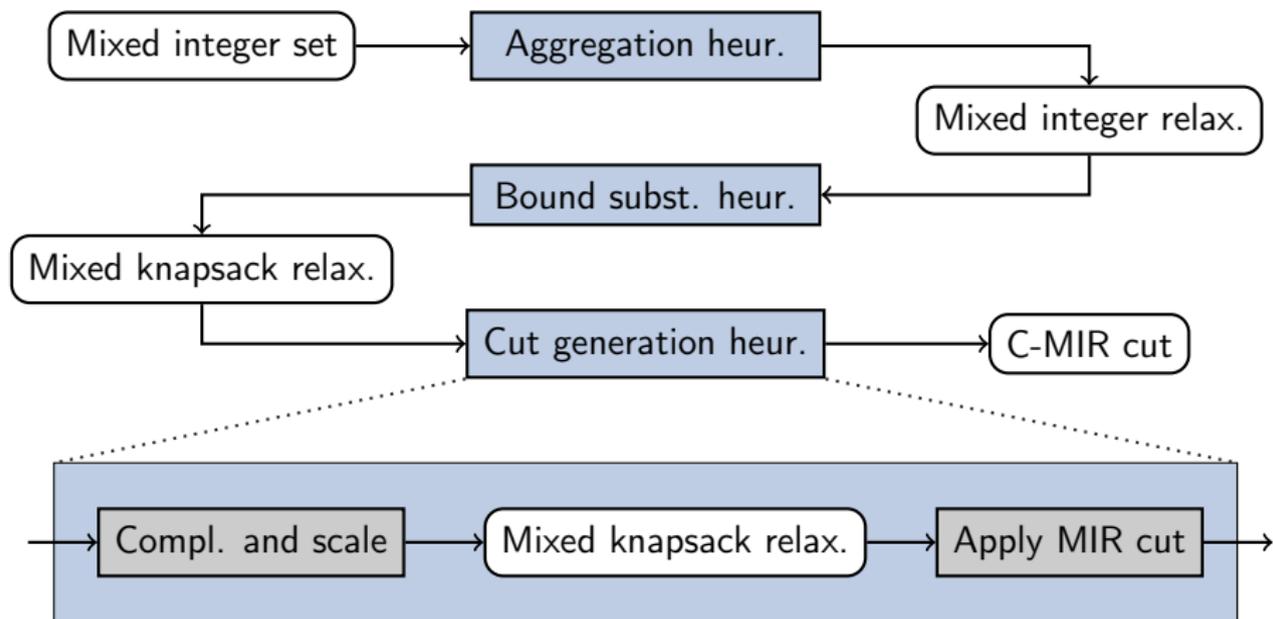
For  $\delta = 4$ ,  $x_1 = 2 - \bar{x}_1$ :

$$\triangleright -\frac{1}{4} \bar{x}_1 + x_2 \leq \frac{7}{8} + \frac{1}{4} s$$

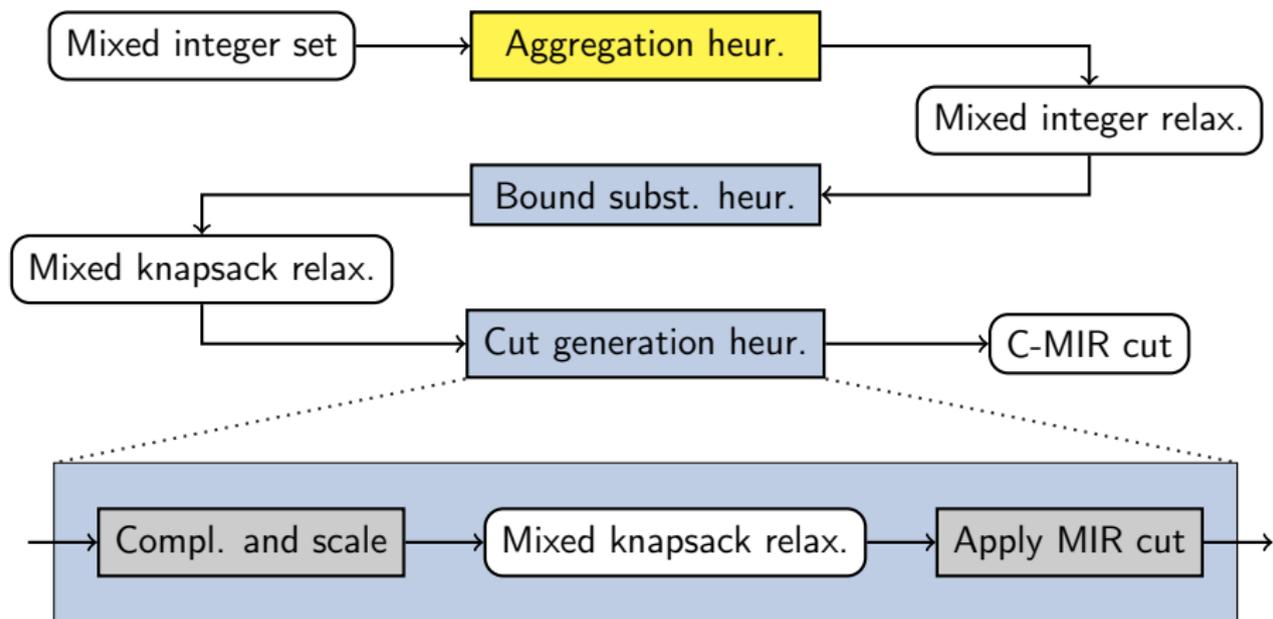
$$\triangleright f_{\frac{7}{8}} = \frac{7}{8} - \lfloor \frac{7}{8} \rfloor = \frac{7}{8}$$



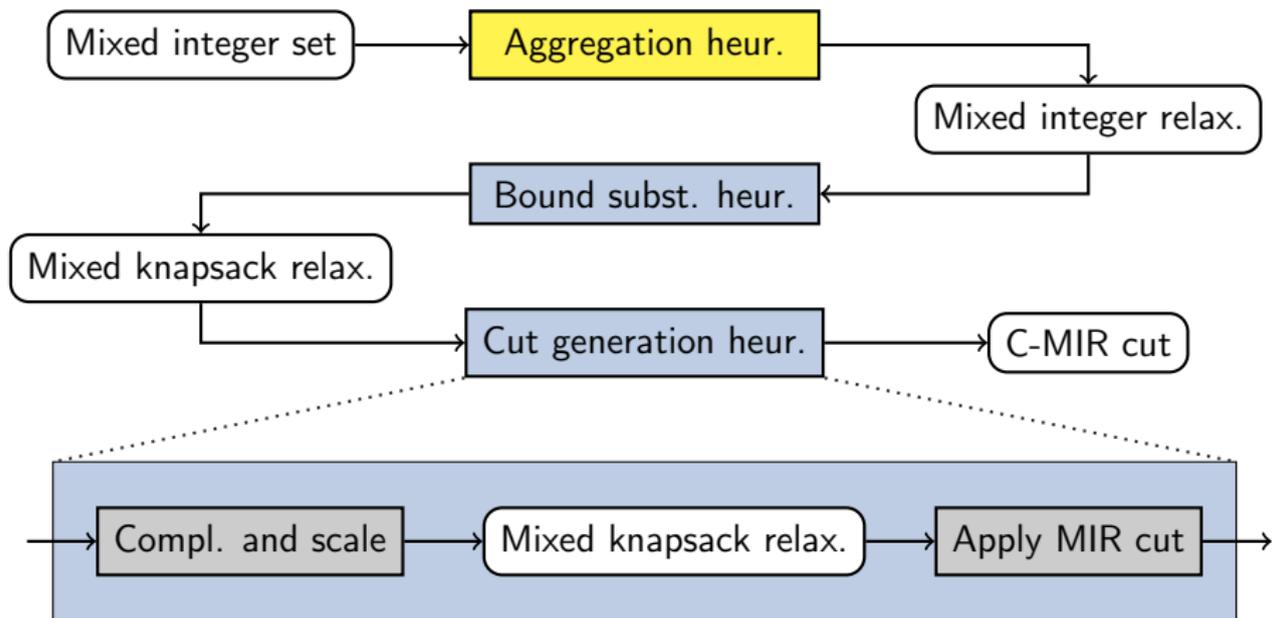
# Outline of the Separation Algorithm



# Outline of the Separation Algorithm

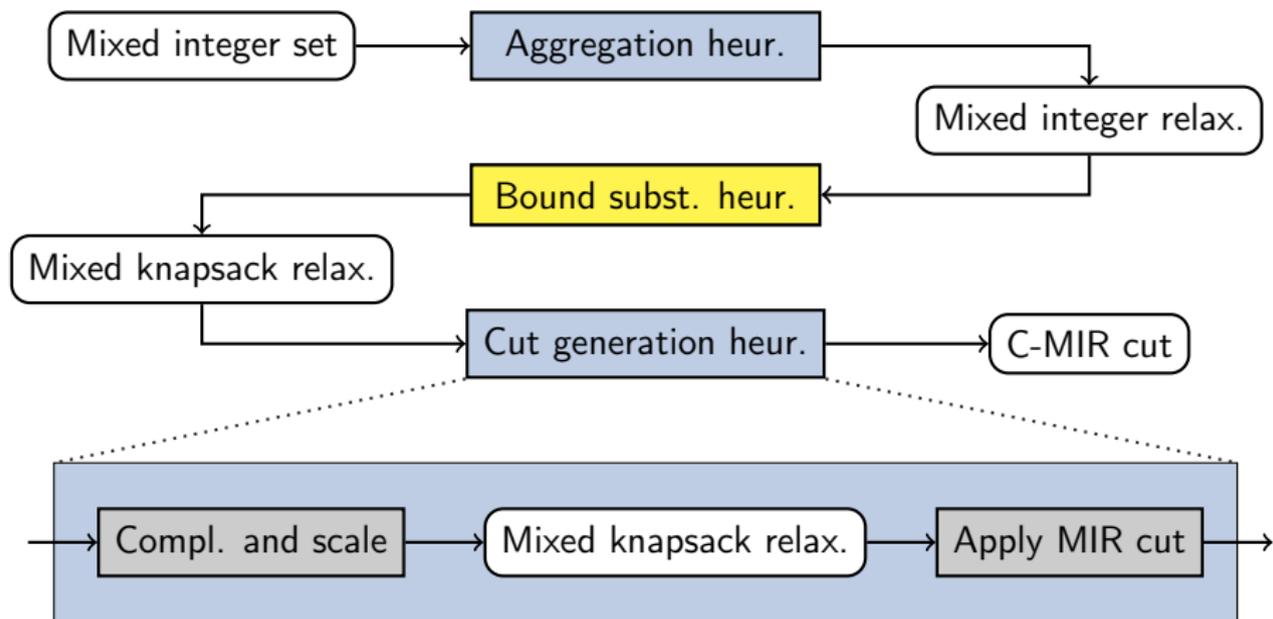


# Outline of the Separation Algorithm

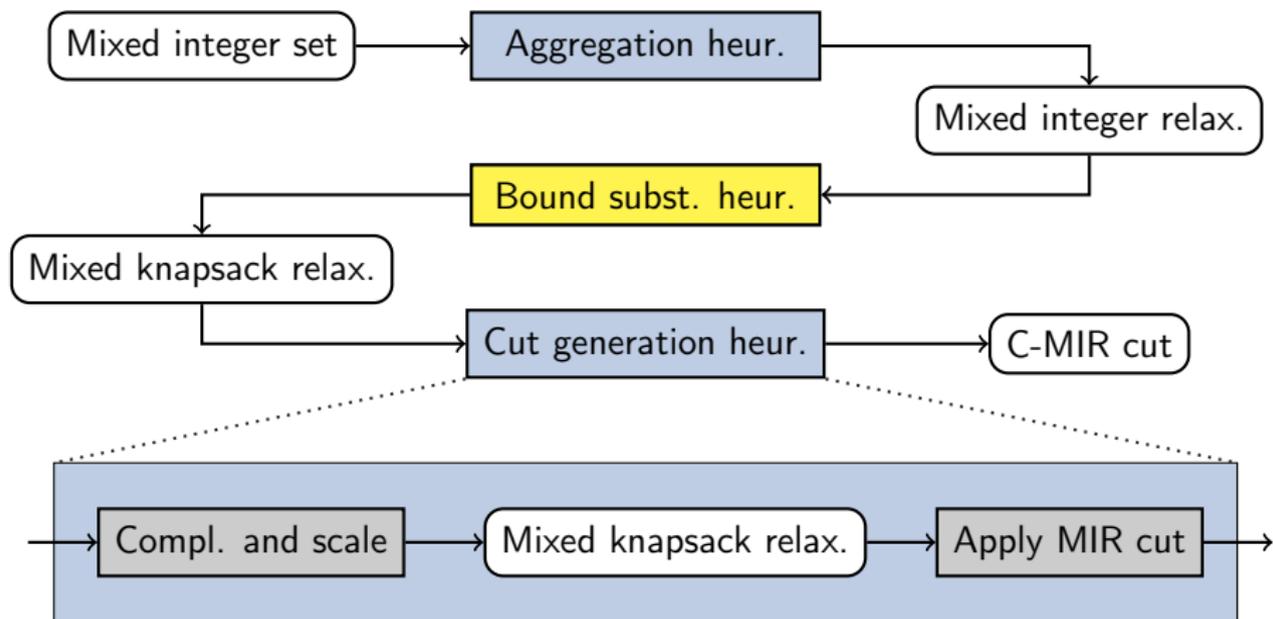


- ▷ Linear combination of constraints defining the mixed integer set

# Outline of the Separation Algorithm

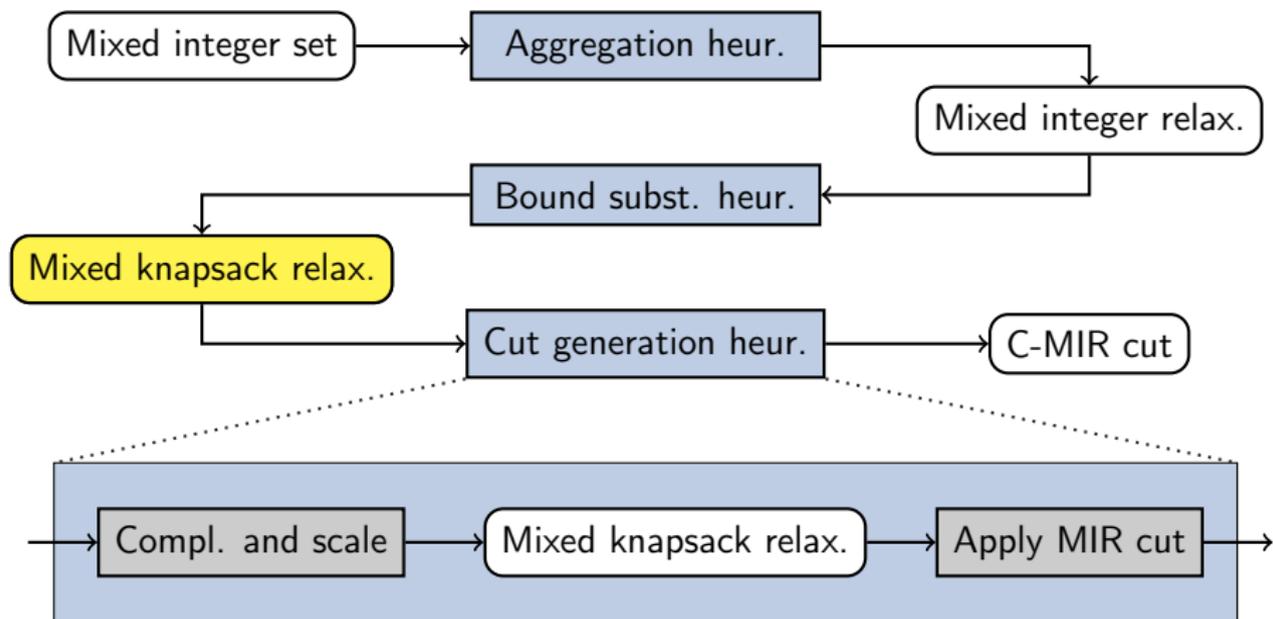


# Outline of the Separation Algorithm

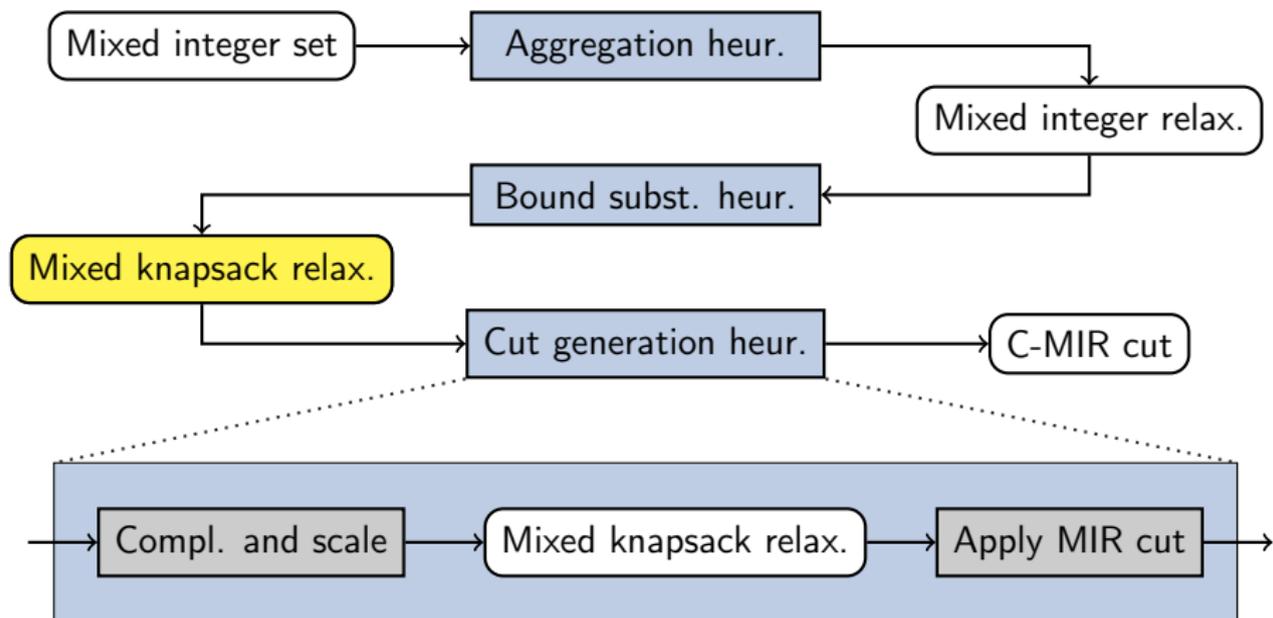


- ▷ Perform bound substitution for all real vars  
(e.g.,  $y_j = l_j + \bar{y}_j$ )
- ▷ Relax corresponding set to a mixed knapsack set

# Outline of the Separation Algorithm

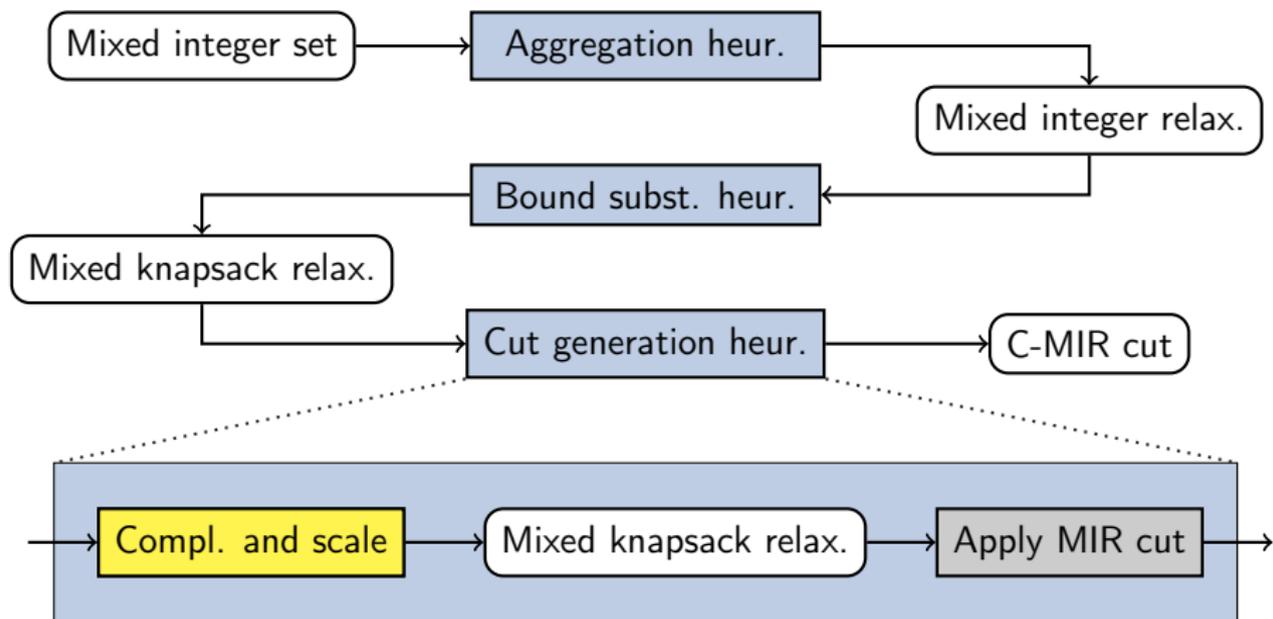


# Outline of the Separation Algorithm

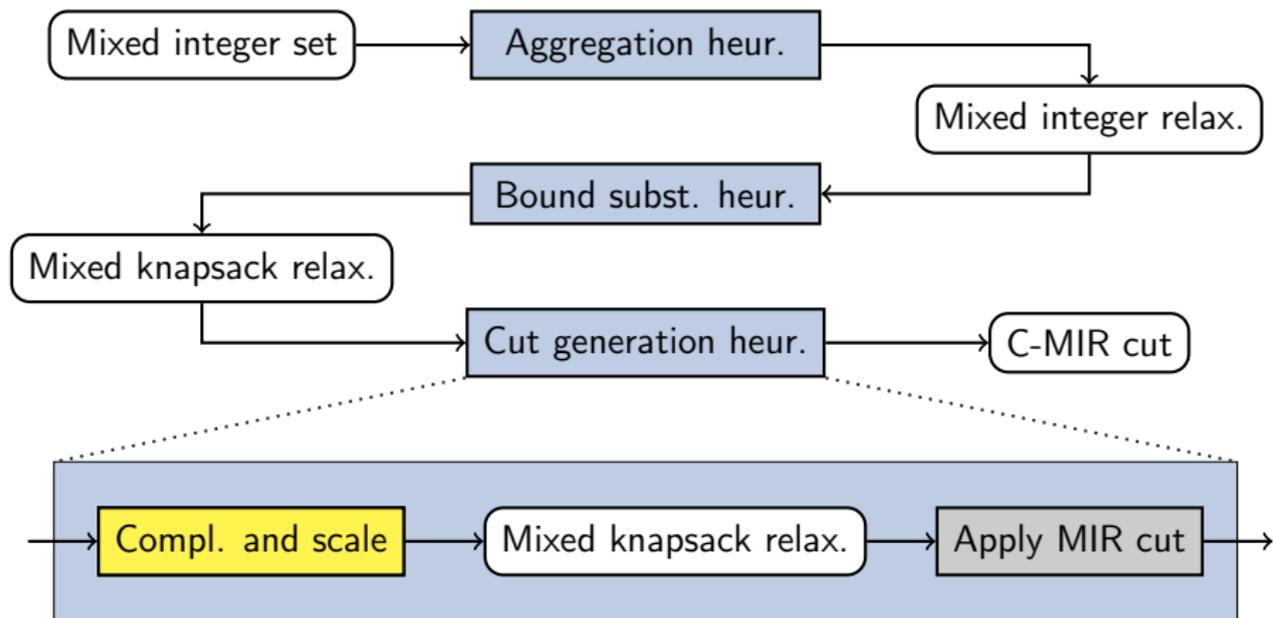


$$\left\{ (x, s) \in \mathbb{Z}_+^n \times \mathbb{R}_+ : \sum_{j \in N} a_j x_j \leq b + s \right. \\ \left. x_j \leq u_j \quad j \in N \right\}$$

# Outline of the Separation Algorithm

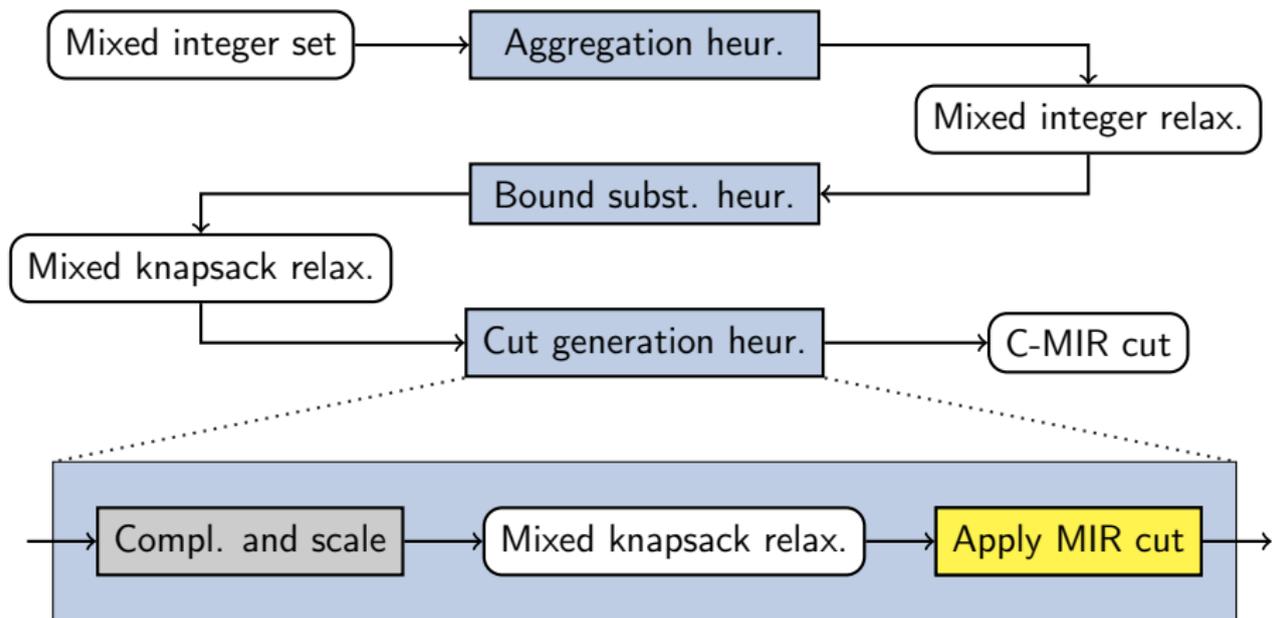


# Outline of the Separation Algorithm

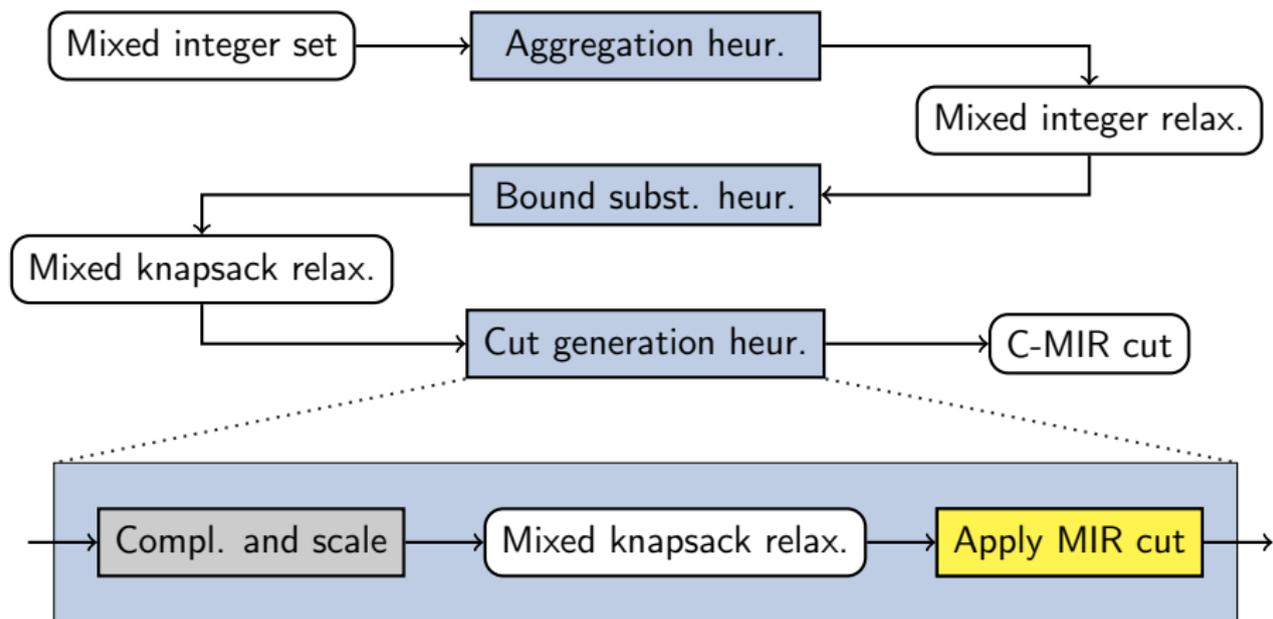


- ▷ Complement some integer vars
- ▷ Divide constraint by  $\delta \in \mathbb{Q}_+ \setminus \{0\}$

# Outline of the Separation Algorithm

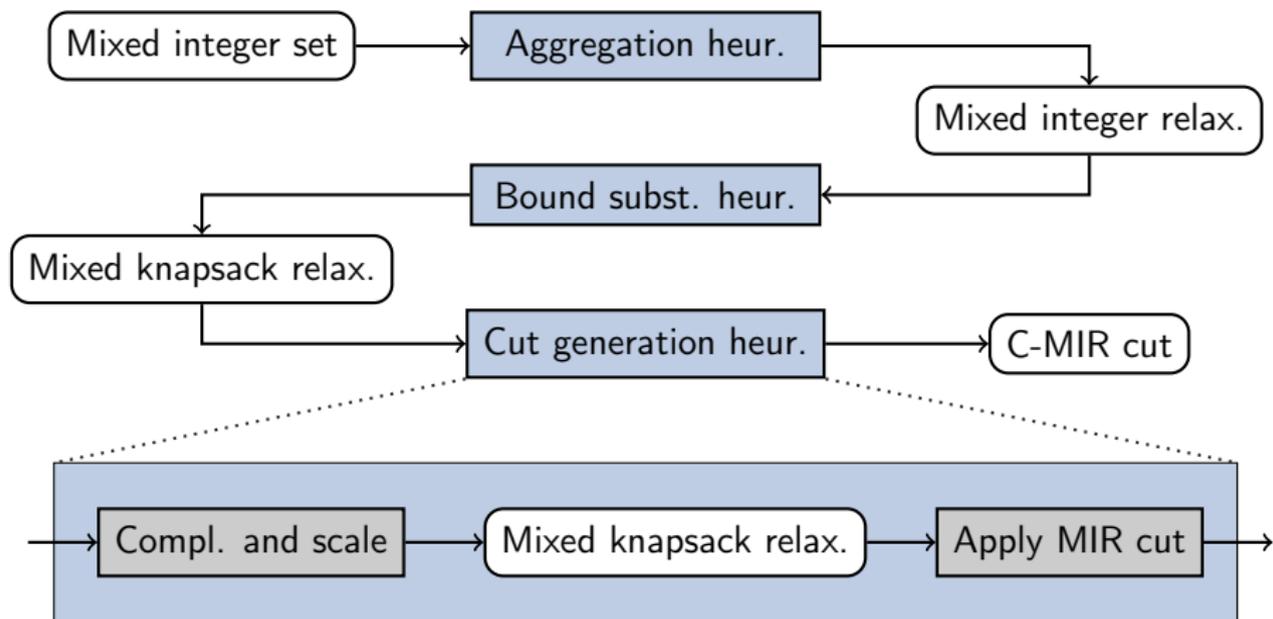


# Outline of the Separation Algorithm



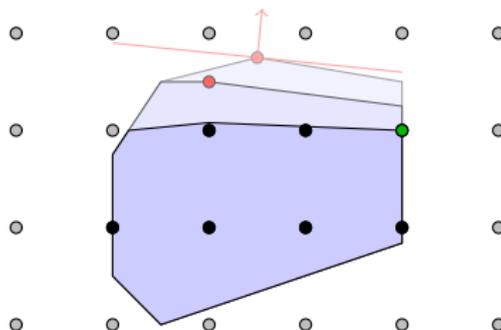
$$\sum_{j \in N} F_{f_b}(a_j)x_j \leq \lfloor b \rfloor + \frac{s}{1 - f_b}$$

# Outline of the Separation Algorithm



## Techniques

- ▷ **General cuts:**
  - ▶ complemented MIR cuts
  - ▶ Gomory mixed integer cuts
  - ▶ strong Chvátal-Gomory cuts
  - ▶  $\{0, \frac{1}{2}\}$ -cuts
  - ▶ implied bound cuts
- ▷ **Problem specific cuts:**
  - ▶ 0-1 knapsack problem
  - ▶ stable set problem
  - ▶ **0-1 single node flow problem**
  - ▶ multi-commodity-flow problem

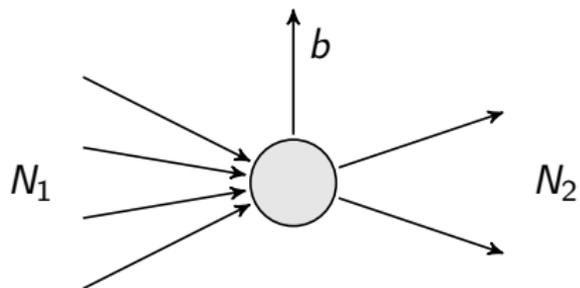


## Results

- ▷ Very **important** component
- ▷ In particular, **c-MIR cuts**
- ▷ **Coordination** important

## Single node with ...

- ▷ external demand of  $b$
- ▷ inflow arcs  $j \in N_1$
- ▷ outflow arcs  $j \in N_2$

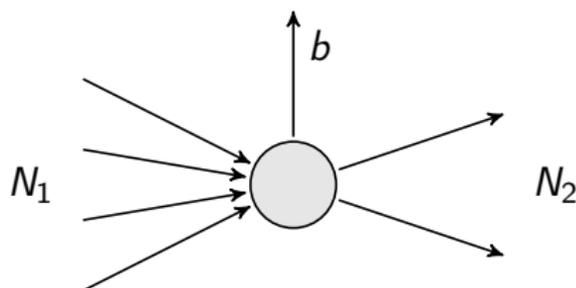


## Single node with ...

- ▷ external demand of  $b$
- ▷ inflow arcs  $j \in N_1$
- ▷ outflow arcs  $j \in N_2$

## Flow has to satisfy ...

- ▷ flow conservation constraint
- ▷ capacities on open arcs



$$\sum_{j \in N_1} y_j - \sum_{j \in N_2} y_j \leq b$$
$$0 \leq y_j \leq u_j x_j$$
$$x_j \in \{0, 1\}$$

$$\{ (x, y) \in \{0, 1\}^n \times \mathbb{R}^n : \sum_{j \in N_1} y_j - \sum_{j \in N_2} y_j \leq b, \\ 0 \leq y_j \leq u_j x_j \text{ for all } j \in N \}$$

- ▷  $(N_1, N_2)$  partition of  $N = \{1, \dots, n\}$
- ▷  $b \in \mathbb{Q}$  and  $u \in \mathbb{Q}_+^n$

Set of arcs s.t. flow conservation constraint is violated, if ...

- ▷ only these arcs are open
- ▷ for each open arc: flow equals capacity

# Basic Structure

Set of arcs s.t. flow conservation constraint is violated, if ...

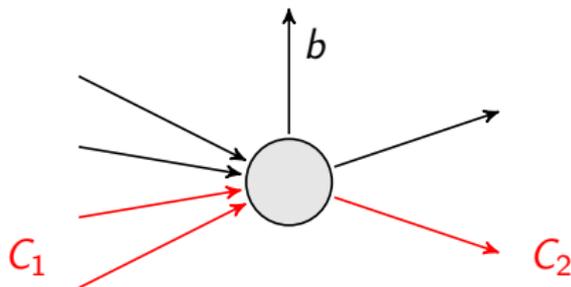
- ▷ only these arcs are open
- ▷ for each open arc: flow equals capacity

Flow cover  $(C_1, C_2)$ :

- ▷  $C_1 \subseteq N_1$  and  $C_2 \subseteq N_2$

$$\text{▷ } \sum_{j \in C_1} u_j - \sum_{j \in C_2} u_j = b + \lambda,$$

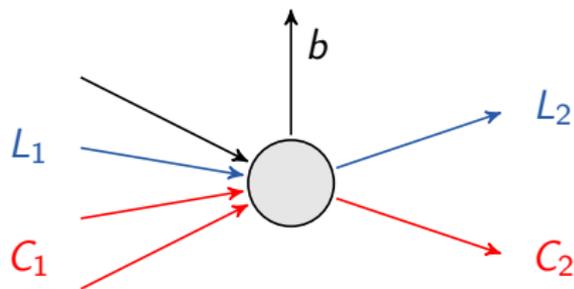
where  $\lambda > 0$ .



# Generalized Flow Cover Inequality (GFCI)

## Basis:

- ▷ Flow cover  $(C_1, C_2)$
- ▷ Sets  $L_i \subseteq N_i \setminus C_i$  for  $i = 1, 2$
- ▷ Constant  $\bar{u} \geq \max\{\lambda, \max_{j \in C_1} u_j\}$



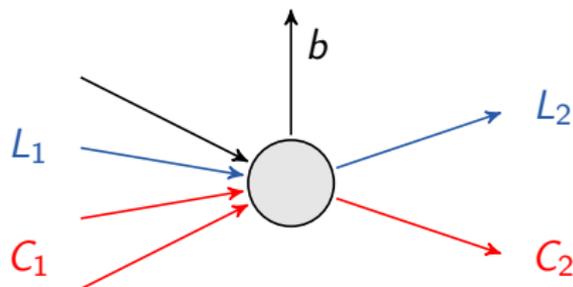
# Generalized Flow Cover Inequality (GFCI)

## Basis:

- ▷ Flow cover  $(C_1, C_2)$
- ▷ Sets  $L_i \subseteq N_i \setminus C_i$  for  $i = 1, 2$
- ▷ Constant  $\bar{u} \geq \max\{\lambda, \max_{j \in C_1} u_j\}$

## Emphasized special cases:

- ▷ SGFCI:  $\bar{u} = \infty, L_1 = \emptyset$
- ▷ EGFCI:  $\bar{u} = \max_{j \in C_1} u_j > \lambda$



# Generalized Flow Cover Inequality (GFCI)

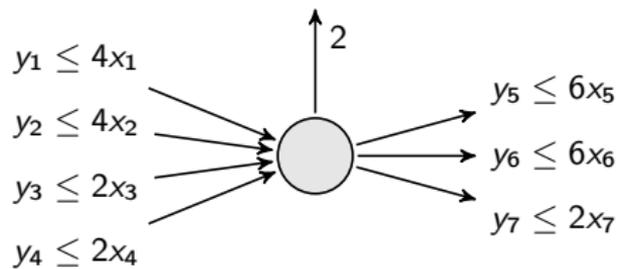
SGFCI ( $\bar{u} = \infty, L_1 = \emptyset$ ):

$$\begin{aligned} & \sum_{j \in C_1} y_j + (u_j - \lambda)^+ (1 - x_j) \\ - & \sum_{j \in C_2} u_j \\ - & \sum_{j \in L_2} \min\{u_j, \lambda\} x_j \\ - & \sum_{j \in N_2 \setminus (C_2 \cup L_2)} y_j \\ \leq & b \end{aligned}$$

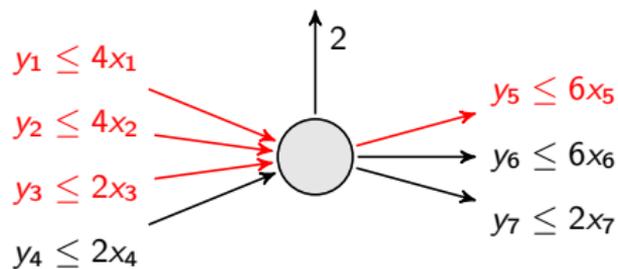
EGFCI ( $\bar{u} = \max_{j \in C_1} u_j > \lambda$ ):

$$\begin{aligned} & \sum_{j \in C_1} y_j + (u_j - \lambda)^+ (1 - x_j) \\ - & \sum_{j \in C_2} u_j - \min\{\lambda, (u_j - \bar{u} + \lambda)^+\} (1 - x_j) \\ + & \sum_{j \in L_1} y_j - (\max\{\bar{u}, u_j\} - \lambda) x_j \\ - & \sum_{j \in L_2} \min\{u_j, \max\{u_j - \bar{u} + \lambda, \lambda\}\} x_j \\ - & \sum_{j \in N_2 \setminus (C_2 \cup L_2)} y_j \\ \leq & b \end{aligned}$$

# Example



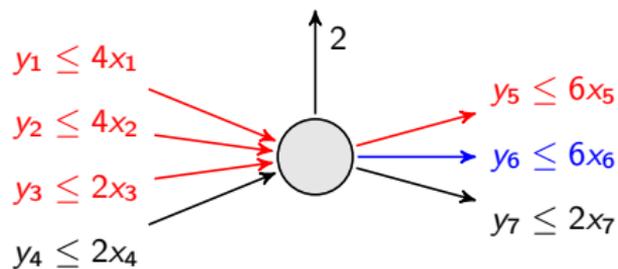
# Example



Flow cover:

$$C_1 = \{1, 2, 3\}, C_2 = \{5\}, \lambda = 2$$

# Example

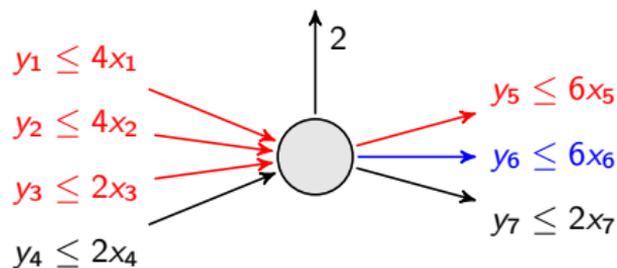


Flow cover:

$$C_1 = \{1, 2, 3\}, C_2 = \{5\}, \lambda = 2$$

$$\text{Sets: } L_1 = \emptyset, L_2 = \{6\}$$

# Example



Flow cover:

$$C_1 = \{1, 2, 3\}, C_2 = \{5\}, \lambda = 2$$

$$\text{Sets: } L_1 = \emptyset, L_2 = \{6\}$$

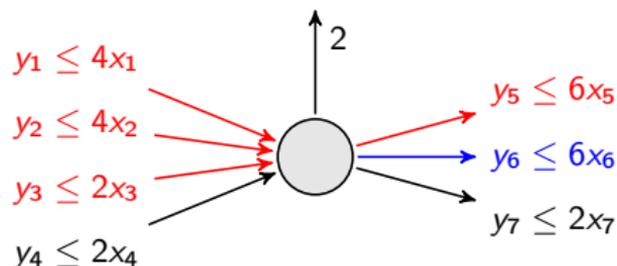
SGFCI ( $\bar{u} = \infty, L_1 = \emptyset$ ):

$$\begin{aligned} & \sum_{j \in C_1} y_j + (u_j - \lambda)^+ (1 - x_j) \\ - & \sum_{j \in C_2} u_j \\ - & \sum_{j \in L_2} \min\{u_j, \lambda\} x_j \\ - & \sum_{j \in N_2 \setminus (C_2 \cup L_2)} y_j \\ \leq & b \end{aligned}$$

EGFCI ( $\bar{u} = \max_{j \in C_1} u_j > \lambda$ ):

$$\begin{aligned} & \sum_{j \in C_1} y_j + (u_j - \lambda)^+ (1 - x_j) \\ - & \sum_{j \in C_2} u_j - \min\{\lambda, (u_j - \bar{u} + \lambda)^+\} (1 - x_j) \\ + & \sum_{j \in L_1} y_j - (\max\{\bar{u}, u_j\} - \lambda) x_j \\ - & \sum_{j \in L_2} \min\{u_j, \max\{u_j - \bar{u} + \lambda, \lambda\}\} x_j \\ - & \sum_{j \in N_2 \setminus (C_2 \cup L_2)} y_j \\ \leq & b \end{aligned}$$

# Example



Flow cover:

$$C_1 = \{1, 2, 3\}, C_2 = \{5\}, \lambda = 2$$

$$\text{Sets: } L_1 = \emptyset, L_2 = \{6\}$$

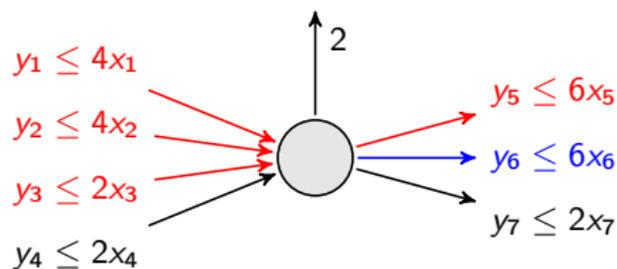
SGFC1 ( $\bar{u} = \infty, L_1 = \emptyset$ ):

$$\begin{aligned} & \sum_{j \in C_1} y_j + (u_j - \lambda)^+ (1 - x_j) \\ - & \sum_{j \in C_2} u_j \\ - & \sum_{j \in L_2} \min\{u_j, \lambda\} x_j \\ - & \sum_{j \in N_2 \setminus (C_2 \cup L_2)} y_j \\ \leq & b \end{aligned}$$

EGFC1 ( $\bar{u} = 4 > 2$ ):

$$\begin{aligned} & \sum_{j \in C_1} y_j + (u_j - \lambda)^+ (1 - x_j) \\ - & \sum_{j \in C_2} u_j - \min\{\lambda, (u_j - \bar{u} + \lambda)^+\} (1 - x_j) \\ + & \sum_{j \in L_1} y_j - (\max\{\bar{u}, u_j\} - \lambda) x_j \\ - & \sum_{j \in L_2} \min\{u_j, \max\{u_j - \bar{u} + \lambda, \lambda\}\} x_j \\ - & \sum_{j \in N_2 \setminus (C_2 \cup L_2)} y_j \\ \leq & b \end{aligned}$$

# Example



Flow cover:

$$C_1 = \{1, 2, 3\}, C_2 = \{5\}, \lambda = 2$$

$$\text{Sets: } L_1 = \emptyset, L_2 = \{6\}$$

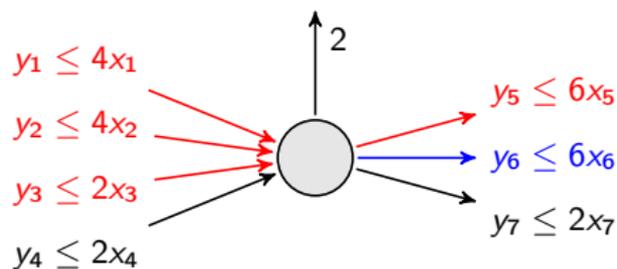
SGFCI ( $\bar{u} = \infty, L_1 = \emptyset$ ):

$$\begin{aligned} & y_1 + 2(1 - x_1) + \\ & y_2 + 2(1 - x_2) + y_3 \\ - & \sum_{j \in C_2} u_j \\ - & \sum_{j \in L_2} \min\{u_j, \lambda\} x_j \\ - & \sum_{j \in N_2 \setminus (C_2 \cup L_2)} y_j \\ \leq & b \end{aligned}$$

EGFCI ( $\bar{u} = 4 > 2$ ):

$$\begin{aligned} & y_1 + 2(1 - x_1) + \\ & y_2 + 2(1 - x_2) + y_3 \\ - & \sum_{j \in C_2} u_j - \min\{\lambda, (u_j - \bar{u} + \lambda)^+\} (1 - x_j) \\ + & \sum_{j \in L_1} y_j - (\max\{\bar{u}, u_j\} - \lambda) x_j \\ - & \sum_{j \in L_2} \min\{u_j, \max\{u_j - \bar{u} + \lambda, \lambda\}\} x_j \\ - & \sum_{j \in N_2 \setminus (C_2 \cup L_2)} y_j \\ \leq & b \end{aligned}$$

# Example



Flow cover:

$$C_1 = \{1, 2, 3\}, C_2 = \{5\}, \lambda = 2$$

$$\text{Sets: } L_1 = \emptyset, L_2 = \{6\}$$

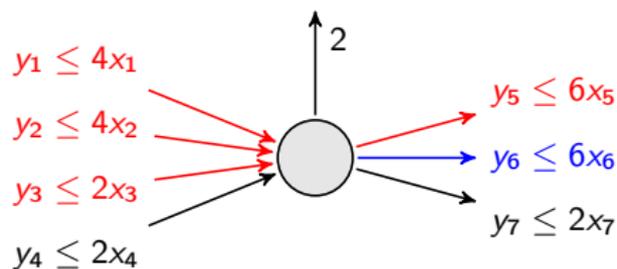
SGFCI ( $\bar{u} = \infty, L_1 = \emptyset$ ):

$$\begin{aligned} & y_1 + 2(1 - x_1) + \\ & y_2 + 2(1 - x_2) + y_3 \\ & - 6 \\ & - \sum_{j \in L_2} \min\{u_j, \lambda\} x_j \\ & - \sum_{j \in N_2 \setminus (C_2 \cup L_2)} y_j \\ & \leq b \end{aligned}$$

EGFCI ( $\bar{u} = 4 > 2$ ):

$$\begin{aligned} & y_1 + 2(1 - x_1) + \\ & y_2 + 2(1 - x_2) + y_3 \\ & - 6 + 2(1 - x_5) \\ & + \sum_{j \in L_1} y_j - (\max\{\bar{u}, u_j\} - \lambda) x_j \\ & - \sum_{j \in L_2} \min\{u_j, \max\{u_j - \bar{u} + \lambda, \lambda\}\} x_j \\ & - \sum_{j \in N_2 \setminus (C_2 \cup L_2)} y_j \\ & \leq b \end{aligned}$$

# Example



Flow cover:

$$C_1 = \{1, 2, 3\}, C_2 = \{5\}, \lambda = 2$$

$$\text{Sets: } L_1 = \emptyset, L_2 = \{6\}$$

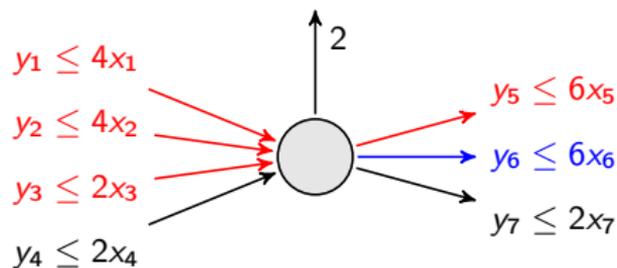
SGFCI ( $\bar{u} = \infty, L_1 = \emptyset$ ):

$$\begin{aligned} & y_1 + 2(1 - x_1) + \\ & y_2 + 2(1 - x_2) + y_3 \\ & - 6 \\ & - \sum_{j \in L_2} \min\{u_j, \lambda\} x_j \\ & - \sum_{j \in N_2 \setminus (C_2 \cup L_2)} y_j \\ & \leq b \end{aligned}$$

EGFCI ( $\bar{u} = 4 > 2$ ):

$$\begin{aligned} & y_1 + 2(1 - x_1) + \\ & y_2 + 2(1 - x_2) + y_3 \\ & - 6 + 2(1 - x_5) \\ & - \sum_{j \in L_2} \min\{u_j, \max\{u_j - \bar{u} + \lambda, \lambda\}\} x_j \\ & - \sum_{j \in N_2 \setminus (C_2 \cup L_2)} y_j \\ & \leq b \end{aligned}$$

# Example



Flow cover:

$$C_1 = \{1, 2, 3\}, C_2 = \{5\}, \lambda = 2$$

$$\text{Sets: } L_1 = \emptyset, L_2 = \{6\}$$

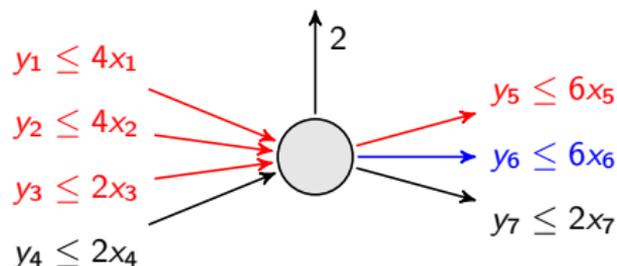
SGFCI ( $\bar{u} = \infty, L_1 = \emptyset$ ):

$$\begin{aligned} & y_1 + 2(1 - x_1) + \\ & y_2 + 2(1 - x_2) + y_3 \\ & - 6 \\ & - 2x_6 \\ & - \sum_{j \in N_2 \setminus (C_2 \cup L_2)} y_j \\ & \leq b \end{aligned}$$

EGFCI ( $\bar{u} = 4 > 2$ ):

$$\begin{aligned} & y_1 + 2(1 - x_1) + \\ & y_2 + 2(1 - x_2) + y_3 \\ & - 6 + 2(1 - x_5) \\ & - 4x_6 \\ & - \sum_{j \in N_2 \setminus (C_2 \cup L_2)} y_j \\ & \leq b \end{aligned}$$

# Example



Flow cover:

$$C_1 = \{1, 2, 3\}, C_2 = \{5\}, \lambda = 2$$

$$\text{Sets: } L_1 = \emptyset, L_2 = \{6\}$$

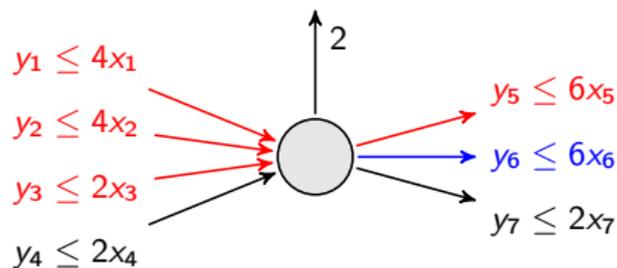
SGFCI ( $\bar{u} = \infty, L_1 = \emptyset$ ):

$$\begin{aligned} & y_1 + 2(1 - x_1) + \\ & y_2 + 2(1 - x_2) + y_3 \\ & - 6 \\ & - 2x_6 \\ & - y_7 \\ & \leq b \end{aligned}$$

EGFCI ( $\bar{u} = 4 > 2$ ):

$$\begin{aligned} & y_1 + 2(1 - x_1) + \\ & y_2 + 2(1 - x_2) + y_3 \\ & - 6 + 2(1 - x_5) \\ & - 4x_6 \\ & - y_7 \\ & \leq b \end{aligned}$$

# Example



Flow cover:

$$C_1 = \{1, 2, 3\}, C_2 = \{5\}, \lambda = 2$$

$$\text{Sets: } L_1 = \emptyset, L_2 = \{6\}$$

SGFCI ( $\bar{u} = \infty, L_1 = \emptyset$ ):

$$\begin{aligned} & y_1 + 2(1 - x_1) + \\ & y_2 + 2(1 - x_2) + y_3 \\ & - 6 \\ & - 2x_6 \\ & - y_7 \\ & \leq 2 \end{aligned}$$

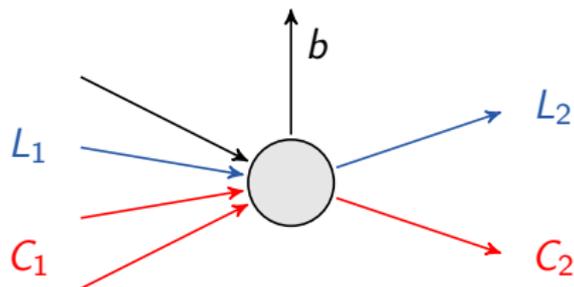
EGFCI ( $\bar{u} = 4 > 2$ ):

$$\begin{aligned} & y_1 + 2(1 - x_1) + \\ & y_2 + 2(1 - x_2) + y_3 \\ & - 6 + 2(1 - x_5) \\ & - 4x_6 \\ & - y_7 \\ & \leq 2 \end{aligned}$$

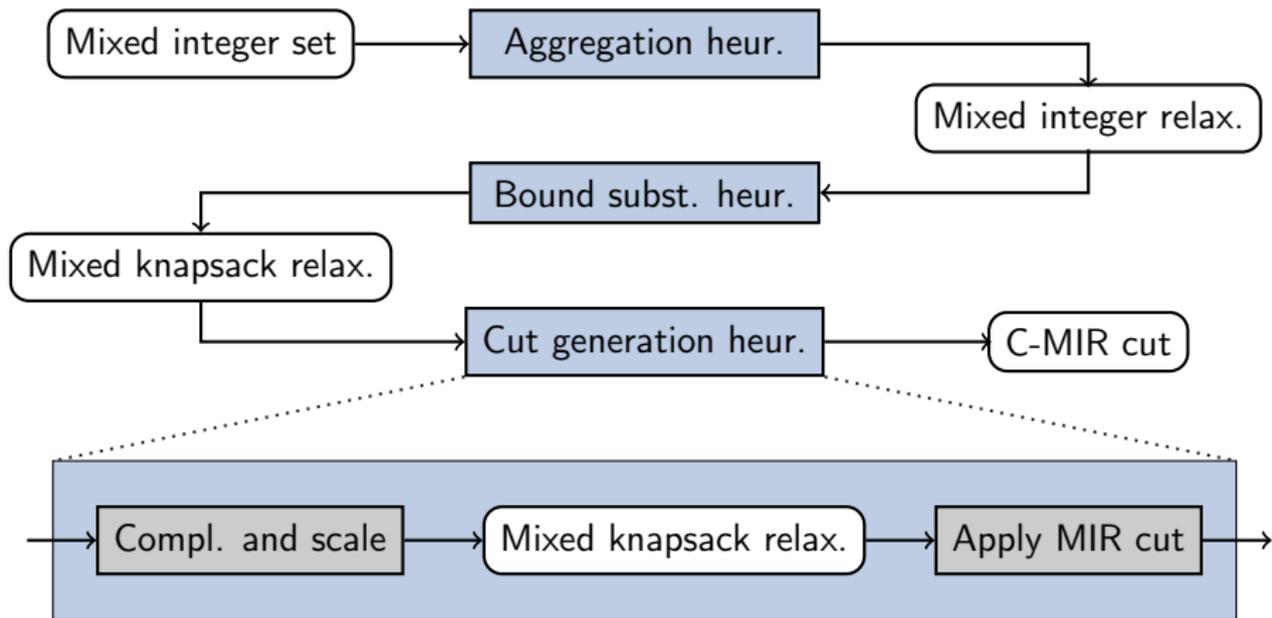
# C-MIR Flow Cover Inequality (C-MIRFCI)

## Basis:

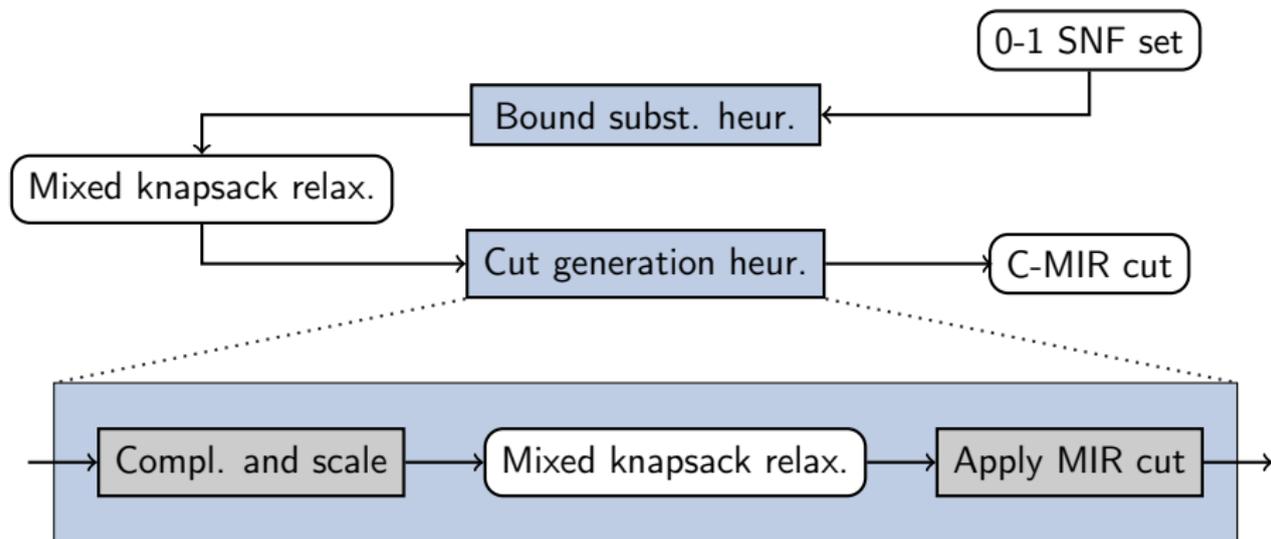
- ▷ Flow cover  $(C_1, C_2)$
- ▷ Sets  $L_i \subseteq N_i \setminus C_i$  for  $i = 1, 2$
- ▷ Constant  $\bar{u} > \lambda$



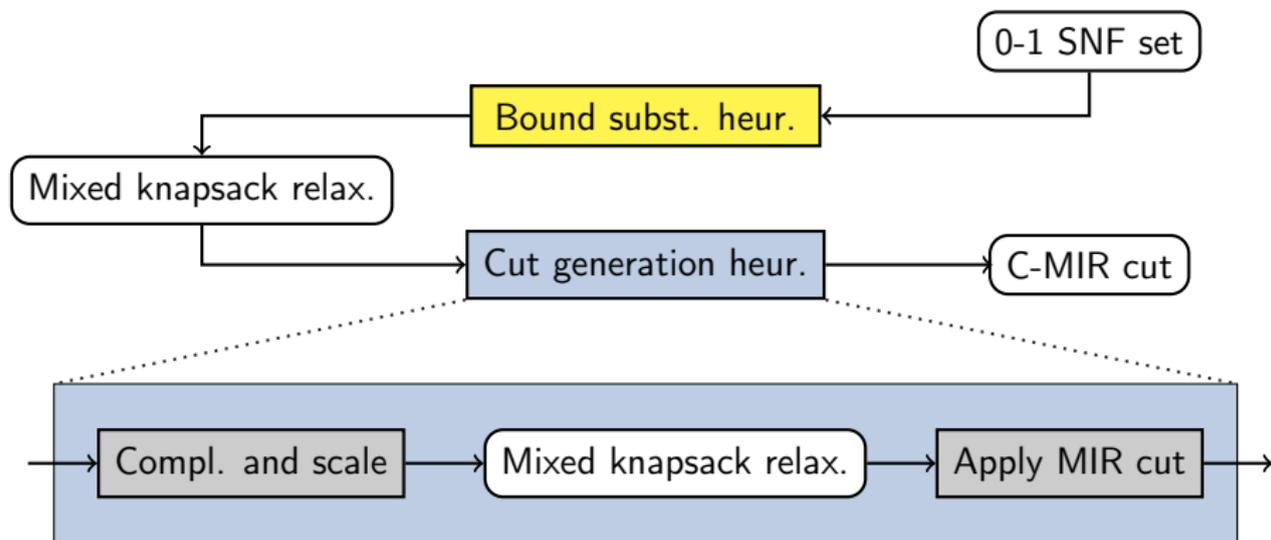
# C-MIR Flow Cover Inequality (C-MIRFCI)



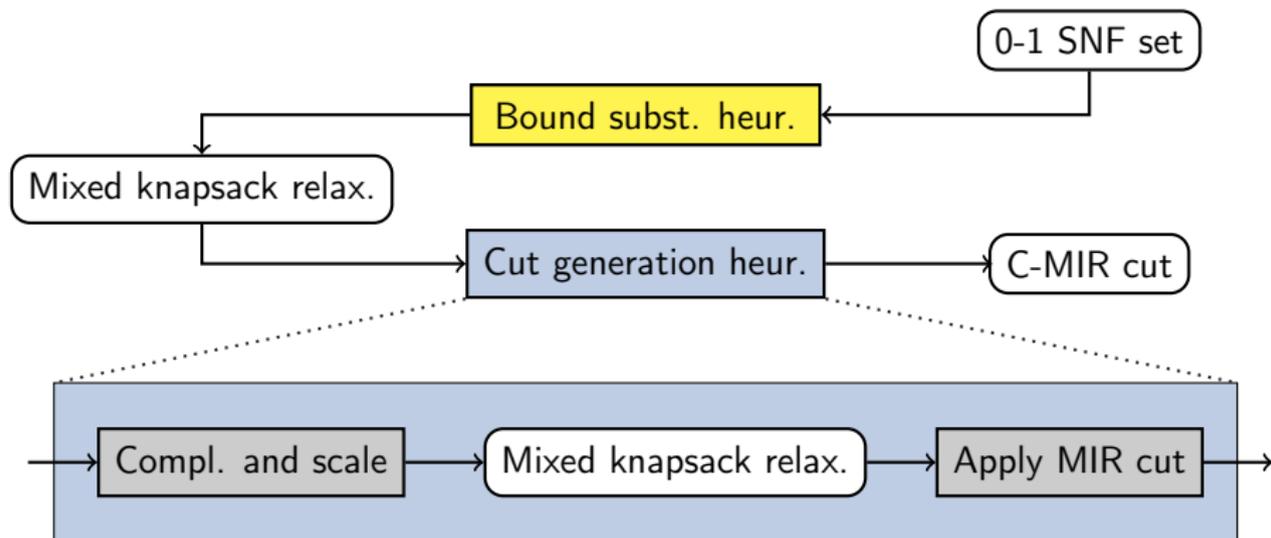
# C-MIR Flow Cover Inequality (C-MIRFCI)



# C-MIR Flow Cover Inequality (C-MIRFCI)

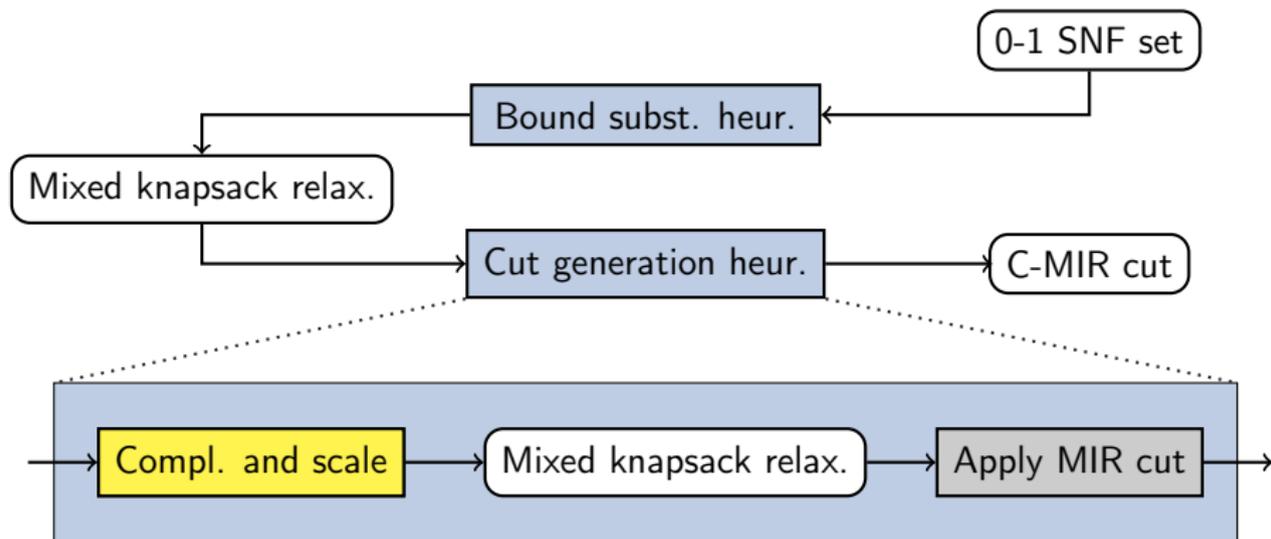


# C-MIR Flow Cover Inequality (C-MIRFCI)

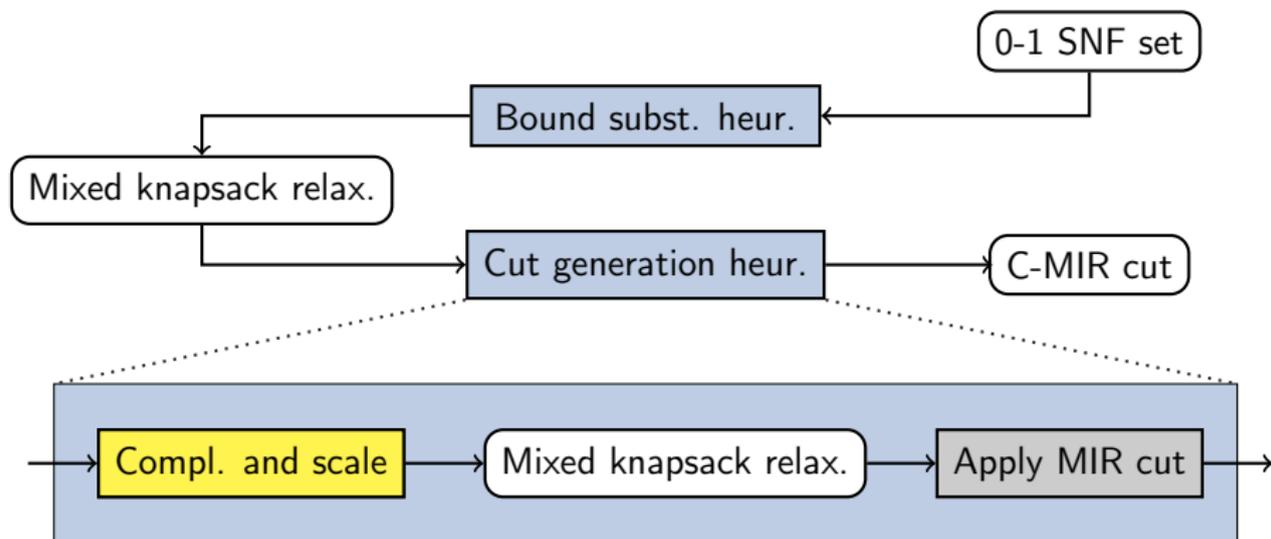


▷ Substitute  $y_j = \begin{cases} u_j x_j - \bar{y}_j & : j \in C_1 \cup C_2 \cup L_1 \cup L_2 \\ 0 + \bar{y}_j & : \text{otherwise} \end{cases}$

# C-MIR Flow Cover Inequality (C-MIRFCI)

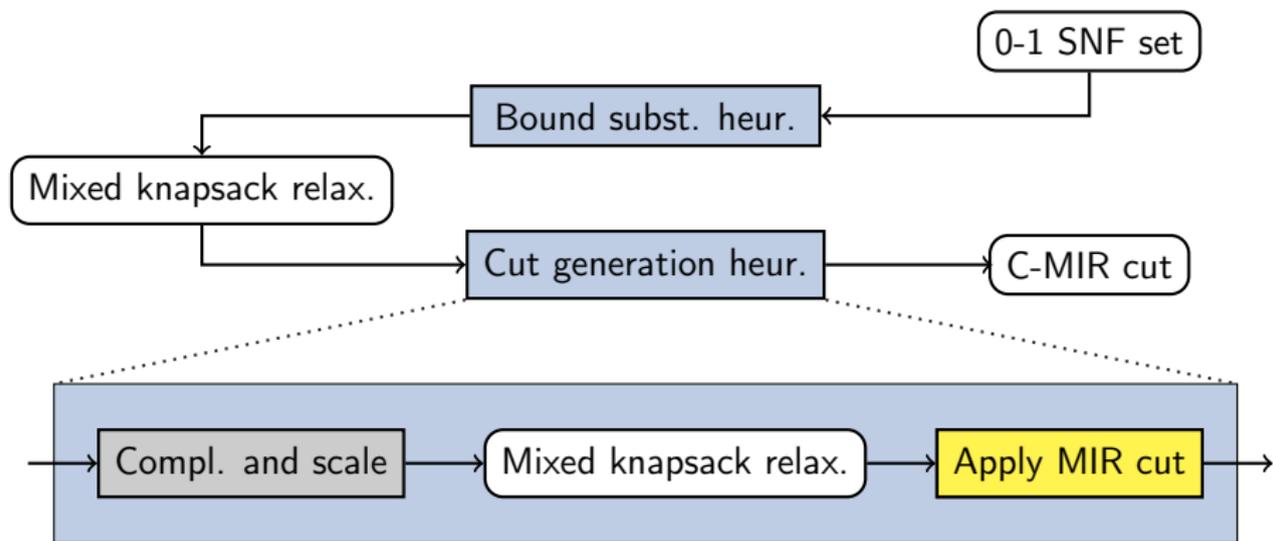


# C-MIR Flow Cover Inequality (C-MIRFCI)

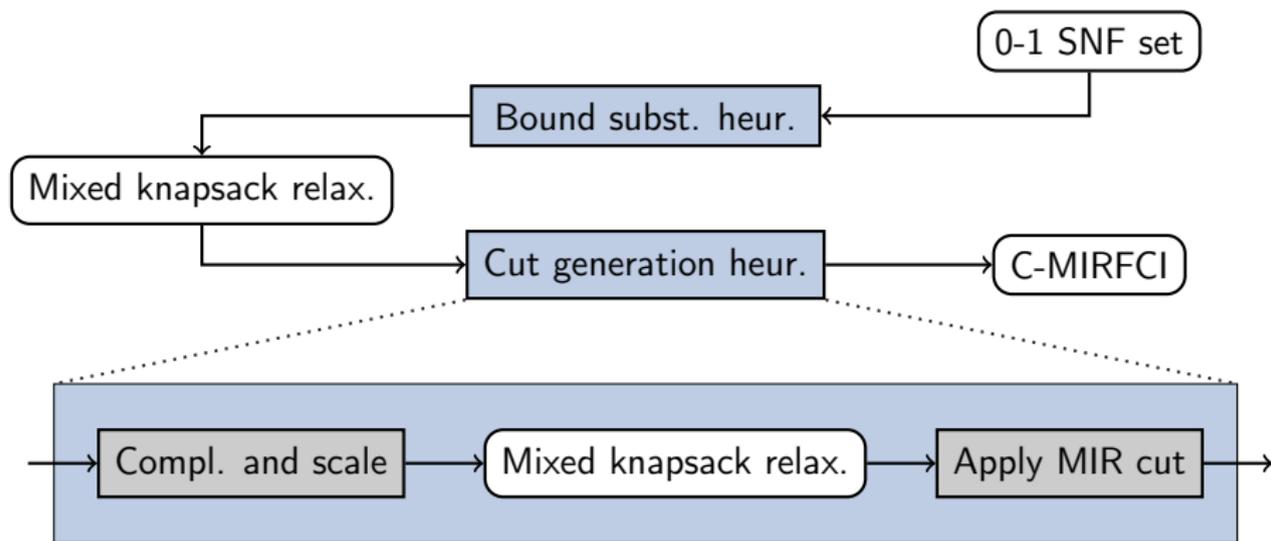


- ▷ Complement all integer vars in  $U = C_1 \cup C_2$
- ▷ Divide constraint by  $\delta = \bar{u}$

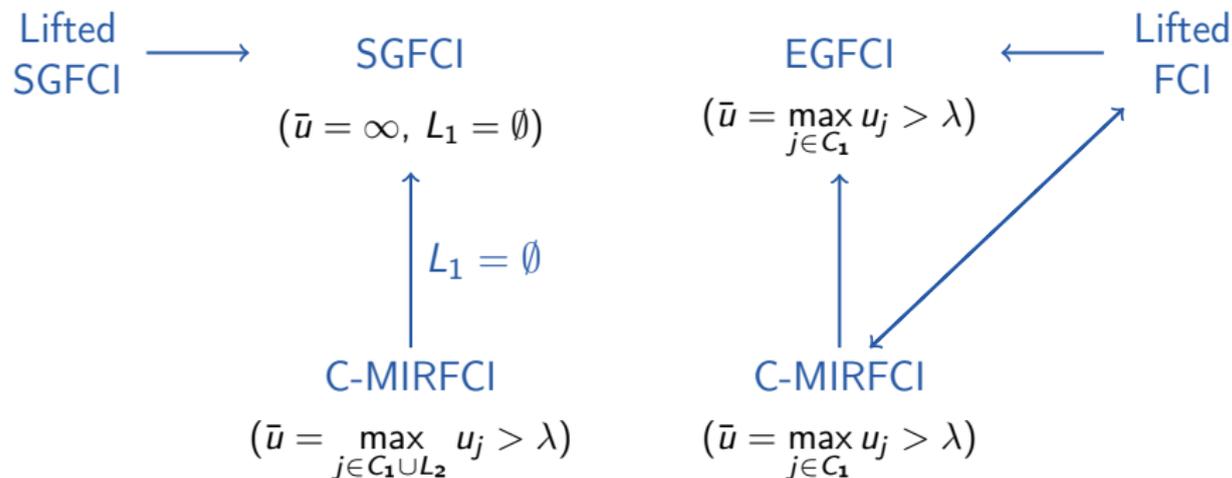
# C-MIR Flow Cover Inequality (C-MIRFCI)



# C-MIR Flow Cover Inequality (C-MIRFCI)



# Dominance Relations



For each MIP row:

1. Construct 0-1 SNF relaxation

- ▶ Similar to the procedure of Van Roy and Wolsey 1986
- ▶ Considers SCIP specific variable bounds

For each MIP row:

1. Construct 0-1 SNF relaxation
2. Determine flow cover  $(C_1, C_2)$

Upper bound on violation  
of weakened SGFCIs:

$$\max \left\{ \sum_{j \in N_1} (x_j^* - 1)z_j + \sum_{j \in N_2} x_j^* z_j : \right. \\ \left. \sum_{j \in N_1} u_j z_j - \sum_{j \in N_2} u_j z_j > b, \right. \\ \left. z_j \in \{0, 1\} \text{ for all } j \in N \right\}$$

For each MIP row:

1. Construct 0-1 SNF relaxation
2. Determine flow cover  $(C_1, C_2)$

**Default:**

- ▷ Exact algorithm  
(after scaling)

**Alternatives:**

- ▷ Heuristic
- ▷ Select algo depending  
on rhs of scaled cons

**Extension:**

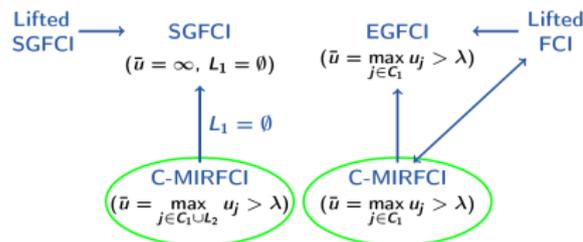
- ▷ Fixing strategy

# Outline of the Separation Algorithm

For each MIP row:

1. Construct 0-1 SNF relaxation
2. Determine flow cover  $(C_1, C_2)$
3. For different values of  $\bar{u}$ :

Default:



Extended candidate set:

- ▷  $u_j > \lambda$  for all  $j \in N$
- ▷  $\lambda + 1$
- ▷  $\max_{j \in N} u_j + 1 > \lambda$

For each MIP row:

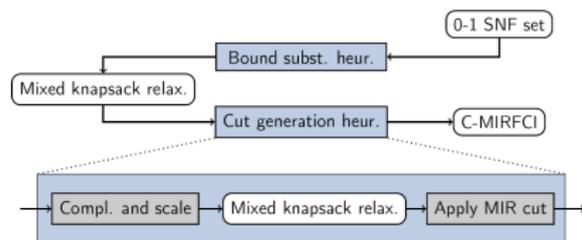
1. Construct 0-1 SNF relaxation
2. Determine flow cover  $(C_1, C_2)$
3. For different values of  $\bar{u}$ :
  - ▶ Determine sets  
 $L_i \subseteq N_i \setminus C_i$  for  $i = 1, 2$

▶ Chosen by comparison.

# Outline of the Separation Algorithm

For each MIP row:

1. Construct 0-1 SNF relaxation
2. Determine flow cover  $(C_1, C_2)$
3. For different values of  $\bar{u}$ :
  - ▶ Determine sets  
 $L_i \subseteq N_i \setminus C_i$  for  $i = 1, 2$
  - ▶ Derive c-MIRFCI

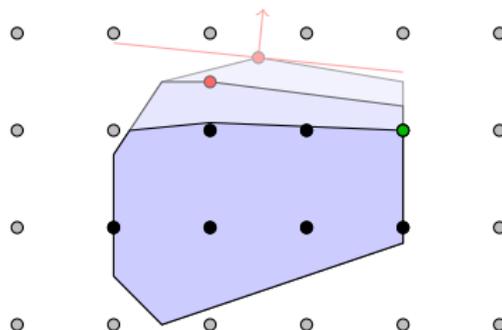


For each MIP row:

1. Construct 0-1 SNF relaxation
2. Determine flow cover  $(C_1, C_2)$
3. For different values of  $\bar{u}$ :
  - ▶ Determine sets  
 $L_i \subseteq N_i \setminus C_i$  for  $i = 1, 2$
  - ▶ Derive c-MIRFCI
4. Select most violated cut

## Techniques

- ▷ **General cuts:**
  - ▶ complemented MIR cuts
  - ▶ Gomory mixed integer cuts
  - ▶ strong Chvátal-Gomory cuts
  - ▶  $\{0, \frac{1}{2}\}$ -cuts
  - ▶ implied bound cuts
- ▷ **Problem specific cuts:**
  - ▶ 0-1 knapsack problem
  - ▶ stable set problem
  - ▶ 0-1 single node flow problem
  - ▶ multi-commodity-flow problem



## Results

- ▷ Very **important** component
- ▷ In particular, **c-MIR cuts**
- ▷ **Coordination** important

# Cut Selection Strategy

▷ **Efficacy**, i.e., distance of the hyperplane to the LP solution

$e_r$

▷ **Orthogonality** with respect to the other cuts

$o_r$

▷ **Parallelism** with respect to the objective function

$p_r$

---

⇒ **Select** cuts with largest value of

$$e_r + w_o * o_r + w_p * p_r$$

# Cut Selection Strategy

▷ **Efficacy**, i.e., distance of the hyperplane to the LP solution

$e_r$

▷ **Orthogonality** with respect to the other cuts

$o_r$

▷ **Parallelism** with respect to the objective function

$p_r$

---

⇒ **Select** cuts with largest value of

$$e_r + w_o * o_r + w_p * p_r$$

## Consequence

▷ Cut as deep as possible into the current LP polyhedron

▷ Select cuts that are pairwise almost orthogonal

▷ Prefer cuts that are close to being parallel to the objective function

# Cut Selection Strategy

▷ **Efficacy**, i.e., distance of the hyperplane to the LP solution

$e_r$

▷ **Orthogonality** with respect to the other cuts

$o_r$

▷ **Parallelism** with respect to the objective function

$p_r$

---

⇒ **Select** cuts with largest value of

$$e_r + w_o * o_r + w_p * p_r$$

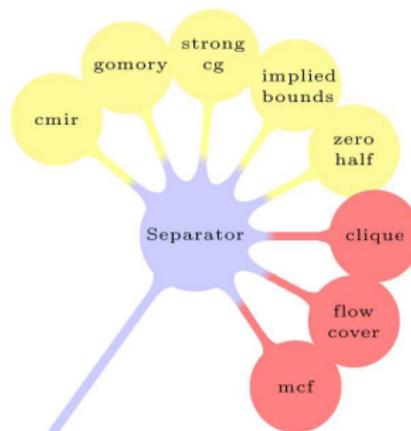
Weights of the criteria can be adjusted

▷ ORTHOFAC = 1.0

▷ OBJPARALFAC = 0.0001

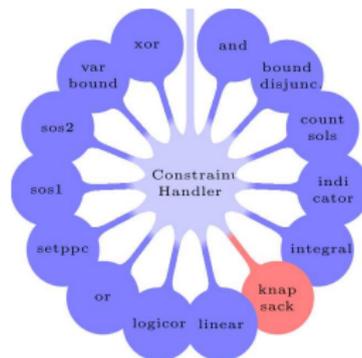
## Separators

- ▷ provide general cuts
- ▷ provide problem specific cuts

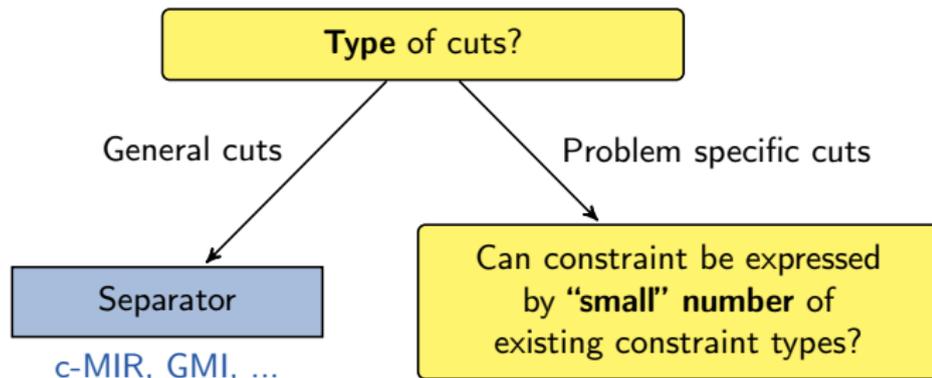


## Constraint handlers

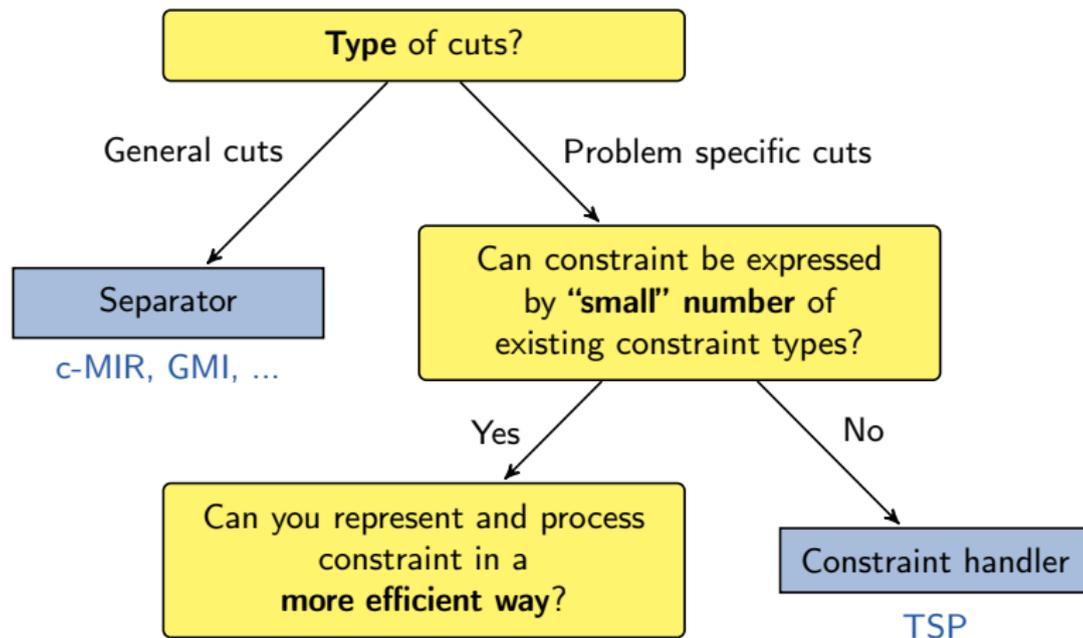
- ▷ feasibility check for given solution
- ▷ provide linear relaxation (in advance or on the fly)
- ▷ additional problem specific cuts



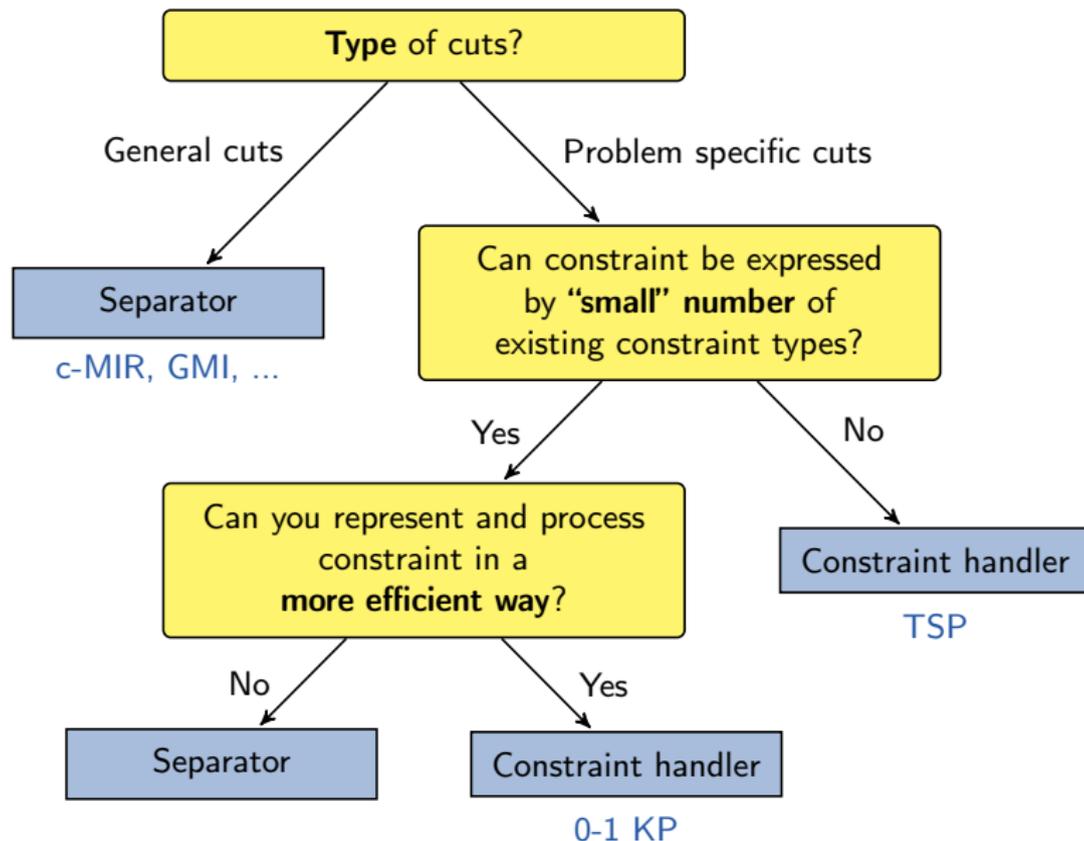
# Separator or Constraint Handler?



# Separator or Constraint Handler?



# Separator or Constraint Handler?



# Cutting Planes and Primal Heuristics

CO@Work Berlin

Timo Berthold and Kati Wolter

09/30/2009



Berlin  
Mathematical  
School



DFG Research Center **MATHEON**  
Mathematics for key technologies



# What are primal heuristics?

Do you have a good idea  
how to construct a feasible  
solution for your problem?



Primal heuristic

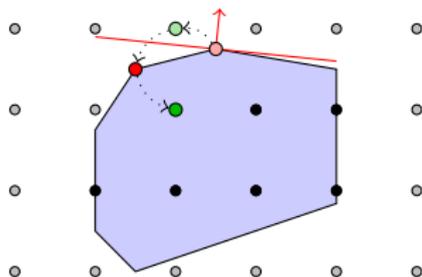
# What are primal heuristics?

Do you have a good idea  
how to construct a feasible  
solution for your problem?

Primal heuristic

## Primal heuristics. . .

- ▷ are incomplete methods which
  - ▷ often find good solutions
  - ▷ within a reasonable time
  - ▷ without any warranty!
- ↪ Integrate into exact solver



## Why use primal heuristics inside an exact solver?

- ▷ Able to prove feasibility of the model
- ▷ Often nearly optimal solutions suffice in practice
- ▷ Feasible solutions guide remaining search process

## Characteristics

## Why use primal heuristics inside an exact solver?

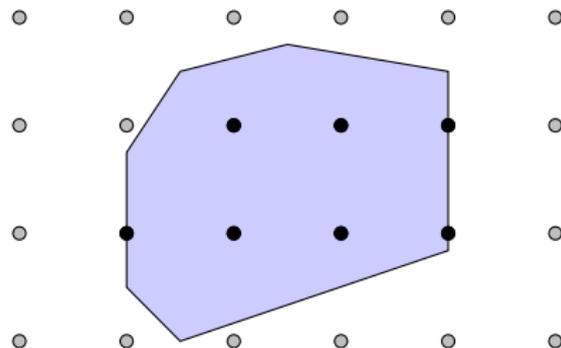
- ▷ Able to prove feasibility of the model
- ▷ Often nearly optimal solutions suffice in practice
- ▷ Feasible solutions guide remaining search process

## Characteristics

- ▷ Main goal: feasible solutions
- ▷ Keep control of effort!
- ▷ Use as much information as you can get

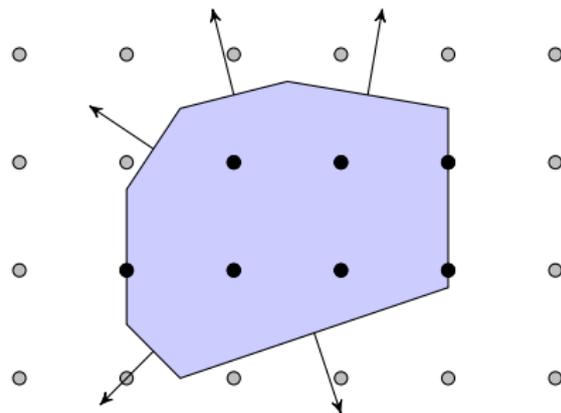
## Statistics & points

- ▷ Variables' locking numbers:  
Potentially violated rows
- ▷ Variables' pseudocosts:  
Average objective change
- ▷ Special points:
  - ▶ LP optimum at root node
  - ▶ Current LP solution
  - ▶ Current best solution
  - ▶ Other known solutions



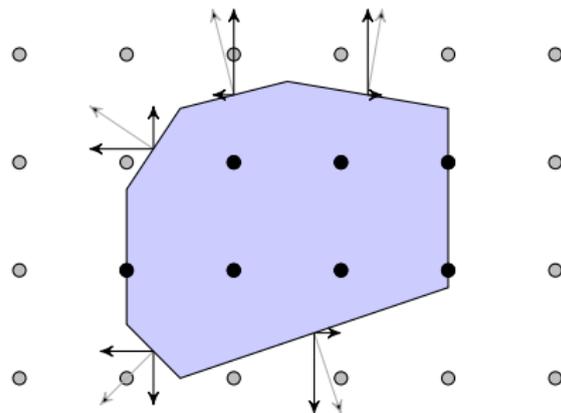
## Statistics & points

- ▷ **Variables' locking numbers:**  
Potentially violated rows
- ▷ **Variables' pseudocosts:**  
Average objective change
- ▷ **Special points:**
  - ▶ LP optimum at root node
  - ▶ Current LP solution
  - ▶ Current best solution
  - ▶ Other known solutions



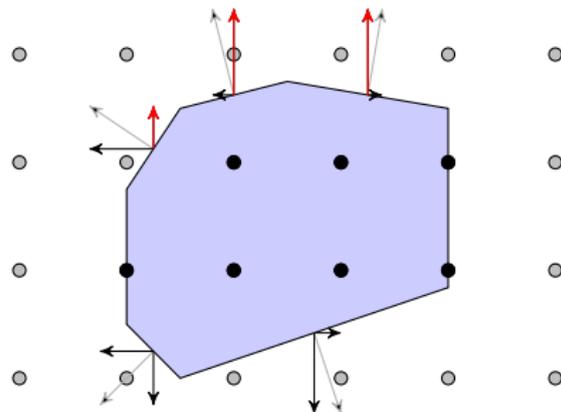
## Statistics & points

- ▷ **Variables' locking numbers:**  
Potentially violated rows
- ▷ **Variables' pseudocosts:**  
Average objective change
- ▷ **Special points:**
  - ▶ LP optimum at root node
  - ▶ Current LP solution
  - ▶ Current best solution
  - ▶ Other known solutions



## Statistics & points

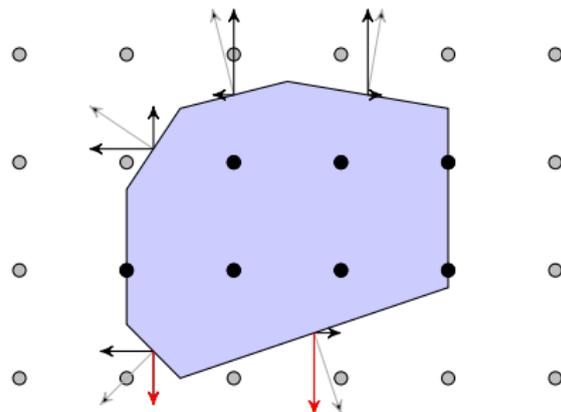
- ▷ Variables' locking numbers:  
Potentially violated rows
- ▷ Variables' pseudocosts:  
Average objective change
- ▷ Special points:
  - ▶ LP optimum at root node
  - ▶ Current LP solution
  - ▶ Current best solution
  - ▶ Other known solutions



```
int nlocks = SCIPvarGetNLocksUp(var);
```

## Statistics & points

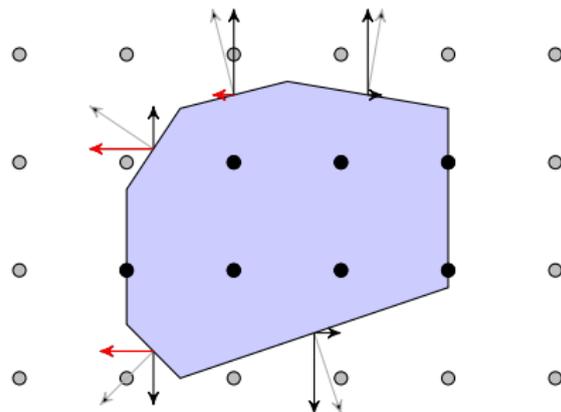
- ▷ **Variables' locking numbers:**  
Potentially violated rows
- ▷ **Variables' pseudocosts:**  
Average objective change
- ▷ **Special points:**
  - ▶ LP optimum at root node
  - ▶ Current LP solution
  - ▶ Current best solution
  - ▶ Other known solutions



```
int nlocks = SCIPvarGetNLocksDown(var);
```

## Statistics & points

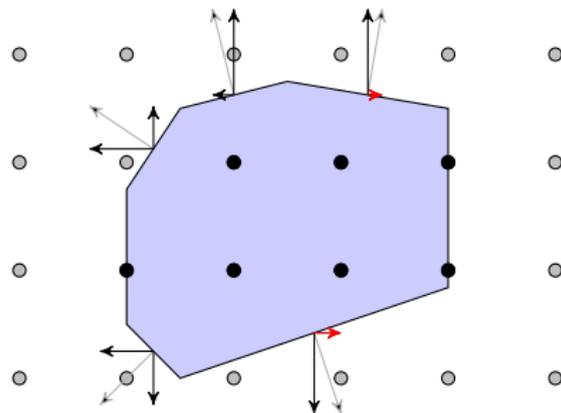
- ▷ **Variables' locking numbers:**  
Potentially violated rows
- ▷ **Variables' pseudocosts:**  
Average objective change
- ▷ **Special points:**
  - ▶ LP optimum at root node
  - ▶ Current LP solution
  - ▶ Current best solution
  - ▶ Other known solutions



```
int nlocks = SCIPvarGetNLocksDown(var);
```

## Statistics & points

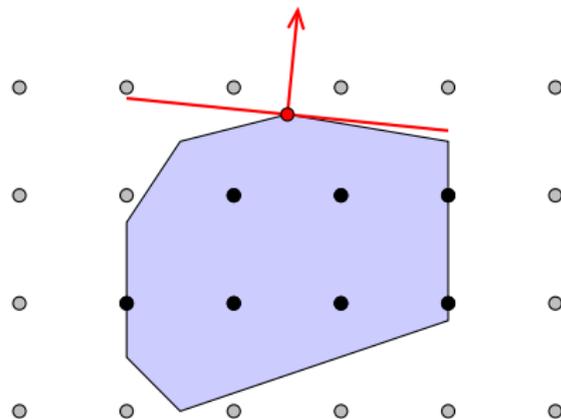
- ▷ **Variables' locking numbers:**  
Potentially violated rows
- ▷ **Variables' pseudocosts:**  
Average objective change
- ▷ **Special points:**
  - ▶ LP optimum at root node
  - ▶ Current LP solution
  - ▶ Current best solution
  - ▶ Other known solutions



```
int nlocks = SCIPvarGetNLocksUp(var);
```

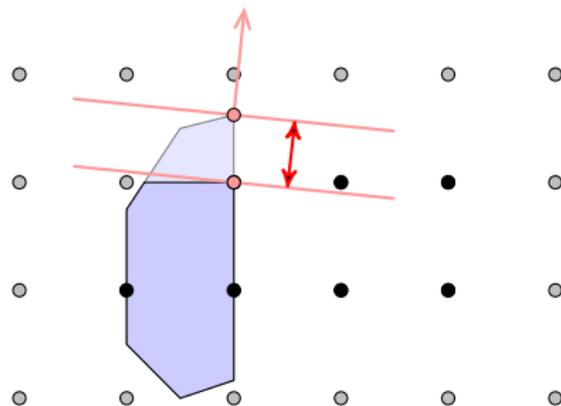
## Statistics & points

- ▷ Variables' locking numbers:  
Potentially violated rows
- ▷ Variables' pseudocosts:  
Average objective change
- ▷ Special points:
  - ▶ LP optimum at root node
  - ▶ Current LP solution
  - ▶ Current best solution
  - ▶ Other known solutions



## Statistics & points

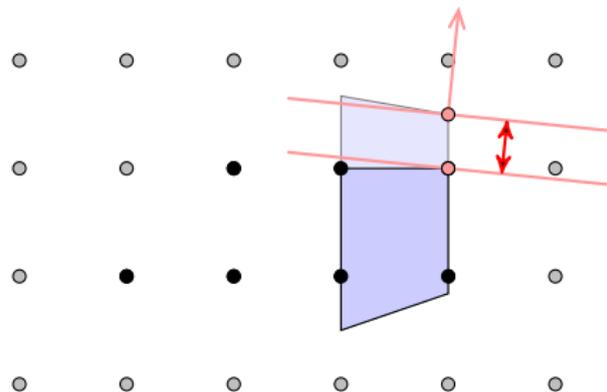
- ▷ Variables' locking numbers:  
Potentially violated rows
- ▷ Variables' pseudocosts:  
Average objective change
- ▷ Special points:
  - ▶ LP optimum at root node
  - ▶ Current LP solution
  - ▶ Current best solution
  - ▶ Other known solutions



```
SCIP_Real pscost = SCIPgetVarPseudocost(scip, var, delta);
```

## Statistics & points

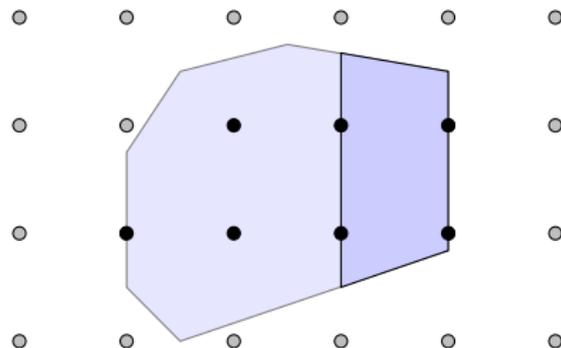
- ▷ Variables' locking numbers:  
Potentially violated rows
- ▷ Variables' pseudocosts:  
Average objective change
- ▷ Special points:
  - ▶ LP optimum at root node
  - ▶ Current LP solution
  - ▶ Current best solution
  - ▶ Other known solutions



```
SCIP_Real pscost = SCIPgetVarPseudocost(scip, var, delta);
```

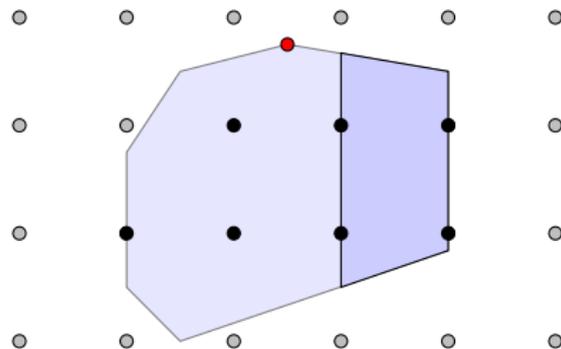
## Statistics & points

- ▷ Variables' locking numbers:  
Potentially violated rows
- ▷ Variables' pseudocosts:  
Average objective change
- ▷ Special points:
  - ▶ LP optimum at root node
  - ▶ Current LP solution
  - ▶ Current best solution
  - ▶ Other known solutions



## Statistics & points

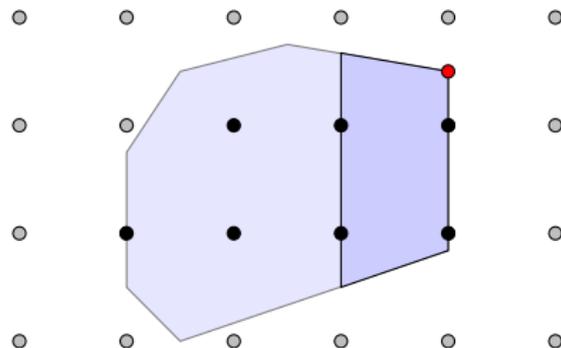
- ▷ Variables' locking numbers:  
Potentially violated rows
- ▷ Variables' pseudocosts:  
Average objective change
- ▷ Special points:
  - ▶ LP optimum at root node
  - ▶ Current LP solution
  - ▶ Current best solution
  - ▶ Other known solutions



```
SCIP_Real rootsolval = SCIPvarGetRootSol(var);
```

## Statistics & points

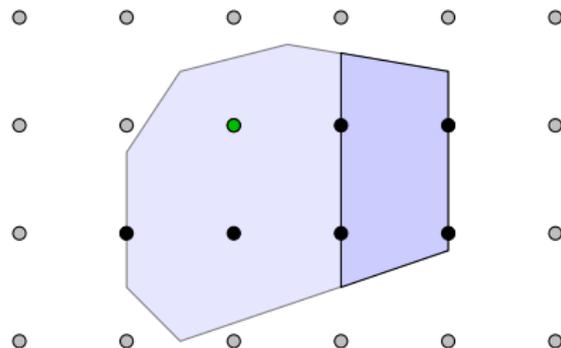
- ▷ Variables' locking numbers:  
Potentially violated rows
- ▷ Variables' pseudocosts:  
Average objective change
- ▷ Special points:
  - ▶ LP optimum at root node
  - ▶ **Current LP solution**
  - ▶ Current best solution
  - ▶ Other known solutions



```
SCIP_Real solval = SCIPgetSolVal(scip, NULL, var);
```

## Statistics & points

- ▷ Variables' locking numbers:  
Potentially violated rows
- ▷ Variables' pseudocosts:  
Average objective change
- ▷ Special points:
  - ▶ LP optimum at root node
  - ▶ Current LP solution
  - ▶ **Current best solution**
  - ▶ Other known solutions

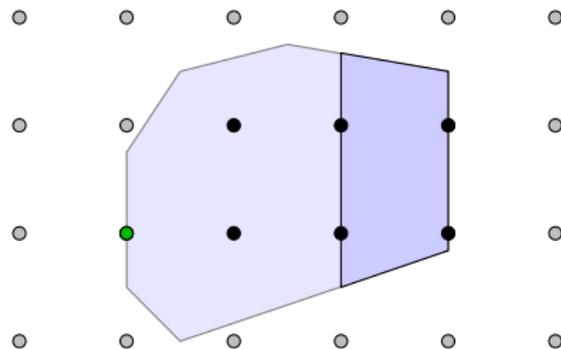


```
SCIP_Sol* bestsol = SCIPgetBestSol(scip);
```

```
SCIP_Real solval = SCIPgetSolVal(scip, bestsol, var);
```

## Statistics & points

- ▷ Variables' locking numbers:  
Potentially violated rows
- ▷ Variables' pseudocosts:  
Average objective change
- ▷ Special points:
  - ▶ LP optimum at root node
  - ▶ Current LP solution
  - ▶ Current best solution
  - ▶ **Other known solutions**



```
SCIP_Sol** sols = SCIPgetSols(scip);  
SCIP_Real solval = SCIPgetSolVal(scip, sols[i], var);
```

## Two main categories

- ▷ Start heuristics
  - ▶ Applied early in the search process
    - ▶ often at root node
  - ▶ Mostly start from LP optimum
- ▷ Improvement heuristics
  - ▶ Require feasible solution
  - ▶ Normally at most once for each incumbent

## Two main categories

- ▷ Start heuristics
  - ▶ Applied early in the search process
    - ▶ often at root node
  - ▶ Mostly start from LP optimum
- ▷ Improvement heuristics
  - ▶ Require feasible solution
  - ▶ Normally at most once for each incumbent

```
#define HEUR_FREQOFS 0
```

## Two main categories

- ▷ Start heuristics
  - ▶ Applied early in the search process
    - ▶ often at root node
  - ▶ **Mostly start from LP optimum**
- ▷ Improvement heuristics
  - ▶ Require feasible solution
  - ▶ Normally at most once for each incumbent

```
if( SCIPgetLPSolstat(scip) != SCIP_LPSOLSTAT_OPTIMAL )  
    return SCIP_OKAY;
```

## Two main categories

- ▷ Start heuristics
  - ▶ Applied early in the search process
    - ▶ often at root node
  - ▶ Mostly start from LP optimum
- ▷ Improvement heuristics
  - ▶ **Require feasible solution**
  - ▶ Normally at most once for each incumbent

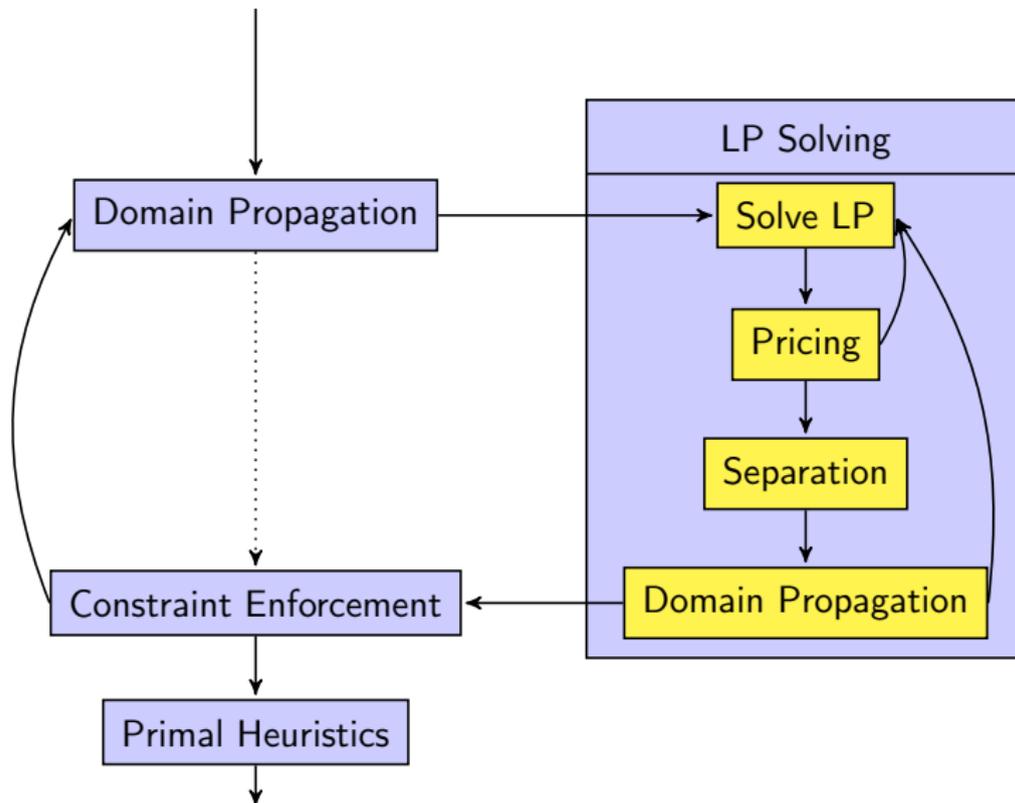
```
if( SCIPgetNSols(scip) <= 0 )  
    return SCIP_OKAY;
```

## Two main categories

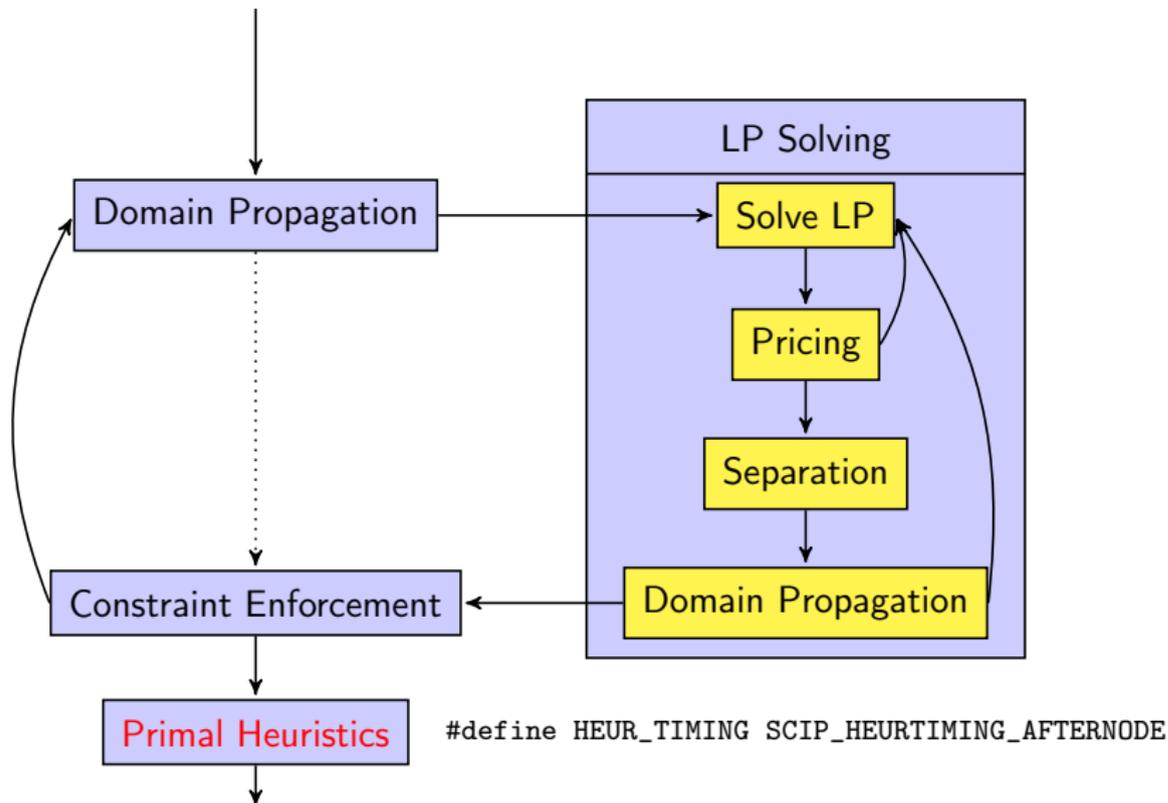
- ▷ Start heuristics
  - ▶ Applied early in the search process
    - ▶ often at root node
  - ▶ Mostly start from LP optimum
- ▷ Improvement heuristics
  - ▶ Require feasible solution
  - ▶ **Normally at most once for each incumbent**

```
struct SCIP_HeurData
{
    SCIP_SOL* lastsol;
}
```

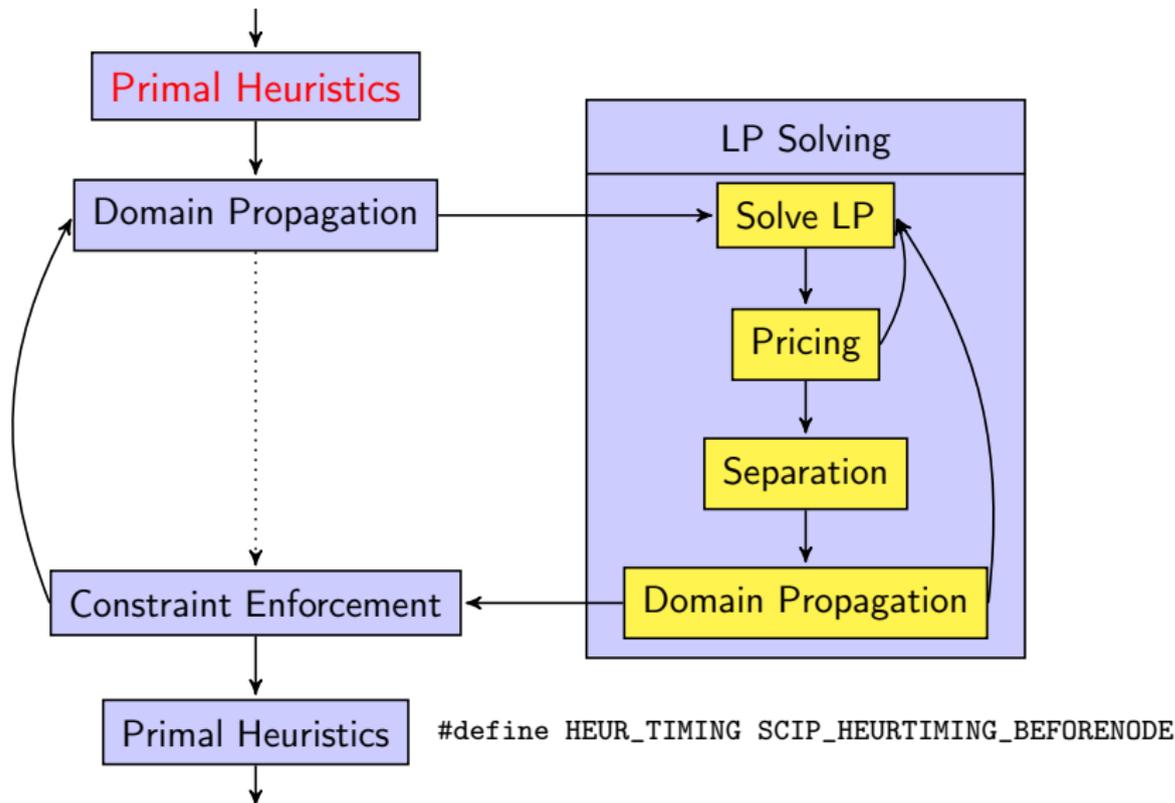
# Heuristic Timings



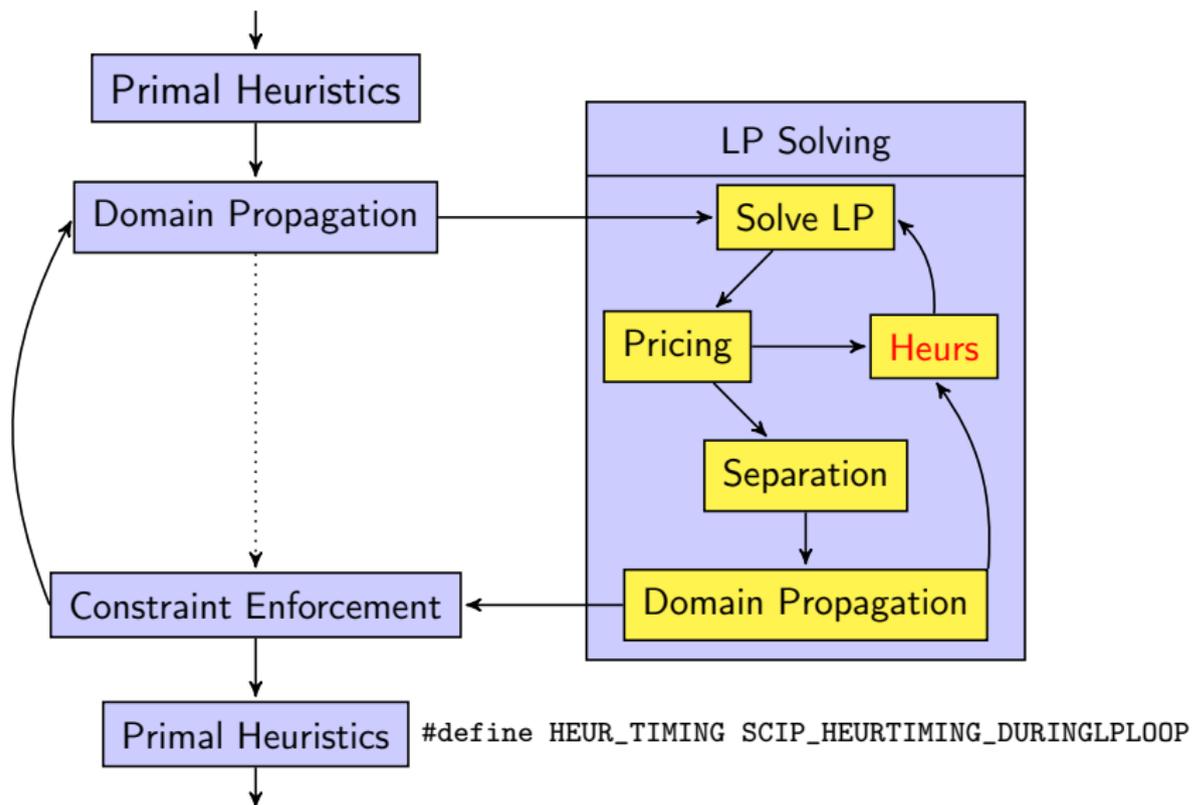
# Heuristic Timings



# Heuristic Timings



# Heuristic Timings



## Approaches

- ▷ **Rounding**: Change fractional to integral values
- ▷ **Diving**: simulate DFS in the branch-and-bound tree using some special branching rule
- ▷ **Objective diving**: manipulate objective function (instead of bounds)
- ▷ **Large Neighborhood Search**: solve some sub-MIP
- ▷ **Pivoting**: manipulate simplex algorithm
- ▷ **Combinatorial**: use special polyhedral properties

## Approaches

- ▷ **Rounding:** Change fractional to integral values
- ▷ **Diving:** simulate DFS in the branch-and-bound tree using some special branching rule
- ▷ **Objective diving:** manipulate objective function (instead of bounds)
- ▷ **Large Neighborhood Search:** solve some sub-MIP
- ▷ **Pivoting:** manipulate simplex algorithm
- ▷ **Combinatorial:** use special polyhedral properties

Guideline: Stay feasible!

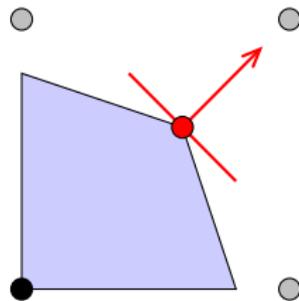
## Features

- ▷ Simple Rounding always stays feasible,
- ▷ Rounding may violate constraints,
- ▷ Shifting may unfix integers,
- ▷ Integer Shifting finally solves an LP.

Guideline: Stay feasible!

## Features

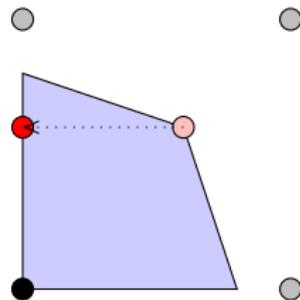
- ▷ Simple Rounding **always stays feasible**,
- ▷ Rounding may violate constraints,
- ▷ Shifting may unfix integers,
- ▷ Integer Shifting finally solves an LP.



Guideline: Stay feasible!

## Features

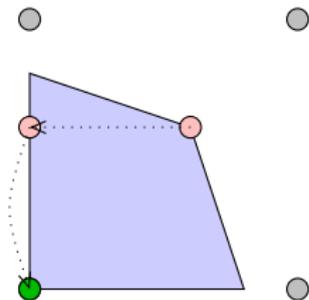
- ▷ Simple Rounding **always stays feasible**,
- ▷ Rounding may violate constraints,
- ▷ Shifting may unfix integers,
- ▷ Integer Shifting finally solves an LP.



Guideline: Stay feasible!

## Features

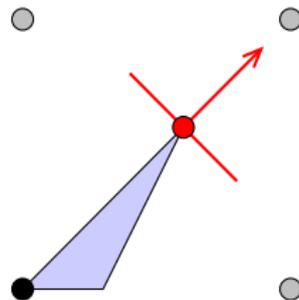
- ▷ Simple Rounding **always stays feasible**,
- ▷ Rounding may violate constraints,
- ▷ Shifting may unfix integers,
- ▷ Integer Shifting finally solves an LP.



Guideline: Stay feasible!

## Features

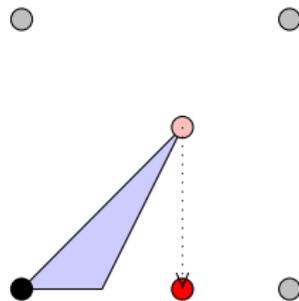
- ▷ Simple Rounding always stays feasible,
- ▷ Rounding **may violate constraints**,
- ▷ Shifting may unfix integers,
- ▷ Integer Shifting finally solves an LP.



Guideline: Stay feasible!

## Features

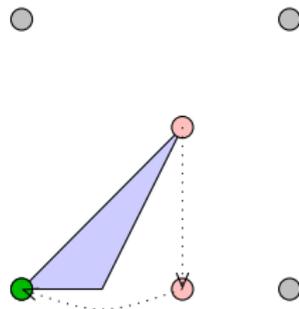
- ▷ Simple Rounding always stays feasible,
- ▷ Rounding **may violate constraints**,
- ▷ Shifting may unfix integers,
- ▷ Integer Shifting finally solves an LP.



Guideline: Stay feasible!

## Features

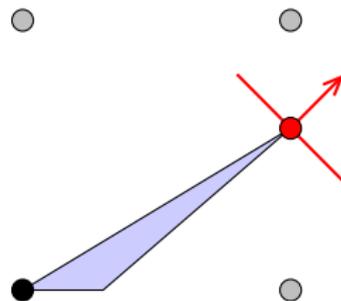
- ▷ Simple Rounding always stays feasible,
- ▷ Rounding **may violate constraints**,
- ▷ Shifting may unfix integers,
- ▷ Integer Shifting finally solves an LP.



Guideline: Stay feasible!

## Features

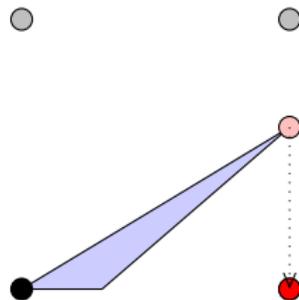
- ▷ Simple Rounding always stays feasible,
- ▷ Rounding may violate constraints,
- ▷ Shifting **may unfix integers**,
- ▷ Integer Shifting finally solves an LP.



Guideline: Stay feasible!

## Features

- ▷ Simple Rounding always stays feasible,
- ▷ Rounding may violate constraints,
- ▷ Shifting may unfix integers,
- ▷ Integer Shifting finally solves an LP.

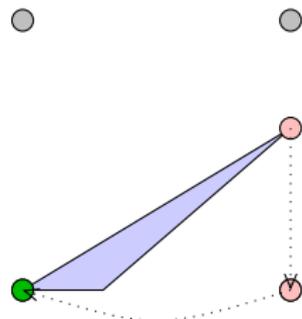


# Rounding Heuristics

Guideline: Stay feasible!

## Features

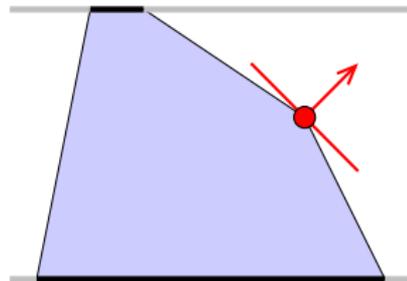
- ▷ Simple Rounding always stays feasible,
- ▷ Rounding may violate constraints,
- ▷ Shifting **may unfix integers**,
- ▷ Integer Shifting finally solves an LP.



Guideline: Stay feasible!

## Features

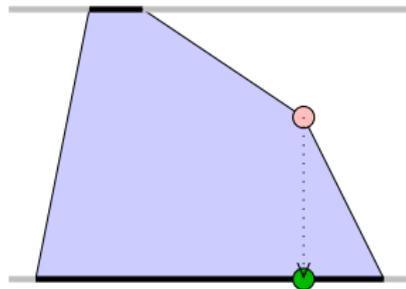
- ▷ Simple Rounding always stays feasible,
- ▷ Rounding may violate constraints,
- ▷ Shifting may unfix integers,
- ▷ Integer Shifting **finally solves an LP.**



Guideline: Stay feasible!

## Features

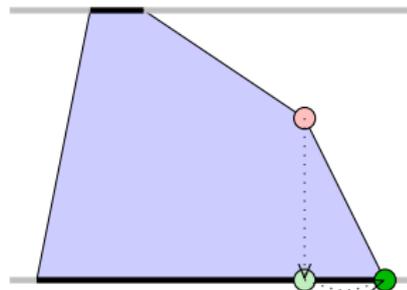
- ▷ Simple Rounding always stays feasible,
- ▷ Rounding may violate constraints,
- ▷ Shifting may unfix integers,
- ▷ Integer Shifting **finally solves an LP.**



Guideline: Stay feasible!

## Features

- ▷ Simple Rounding always stays feasible,
- ▷ Rounding may violate constraints,
- ▷ Shifting may unfix integers,
- ▷ Integer Shifting **finally solves an LP.**



## Approaches

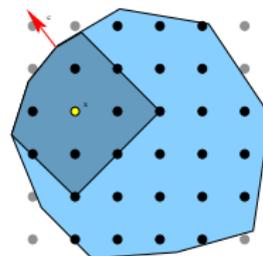
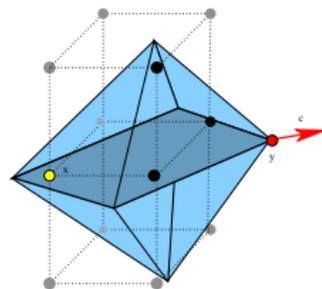
- ▷ **Rounding**: Change fractional to integral values
- ▷ **Diving**: simulate DFS in the branch-and-bound tree using some special branching rule
- ▷ **Objective diving**: manipulate objective function (instead of bounds)
- ▷ **Large Neighborhood Search**: solve some sub-MIP
- ▷ **Pivoting**: manipulate simplex algorithm
- ▷ **Combinatorial**: use special polyhedral properties

# Large Neighborhood Search

## LNS improvement heuristics

- ✓ RINS
- ✓ Local Branching
- ✓ Mutation
- ✓ Crossover

Today: LNS Start Heuristic



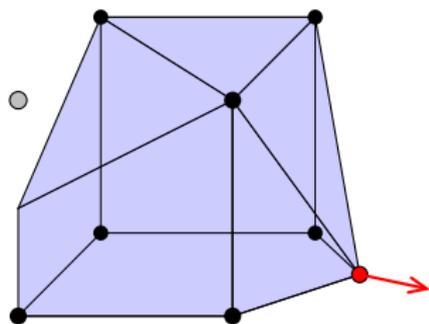
## Algorithm

1.  $\bar{x} \leftarrow$  LP optimum;
2. Fix all integral variables:  
 $x_i := \bar{x}_i$  for all  $i : \bar{x}_i \in \mathbb{Z}$ ;
3. Reduce domain of fractional variables:  
 $x_i \in \{ \lfloor \bar{x}_i \rfloor; \lceil \bar{x}_i \rceil \}$ ;
4. Solve the resulting sub-MIP

# RENS (Relaxation Enforced Neighborhood Search)

## Algorithm

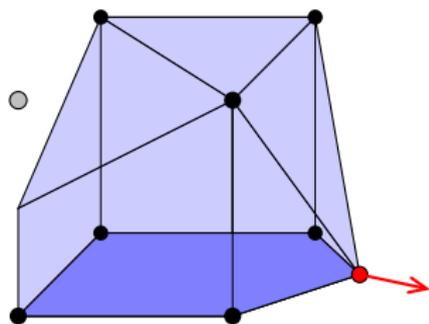
1.  $\bar{x} \leftarrow$  LP optimum;
2. Fix all integral variables:  
 $x_i := \bar{x}_i$  for all  $i : \bar{x}_i \in \mathbb{Z}$ ;
3. Reduce domain of fractional variables:  
 $x_i \in \{\lfloor \bar{x}_i \rfloor; \lceil \bar{x}_i \rceil\}$ ;
4. Solve the resulting sub-MIP



# RENS (Relaxation Enforced Neighborhood Search)

## Algorithm

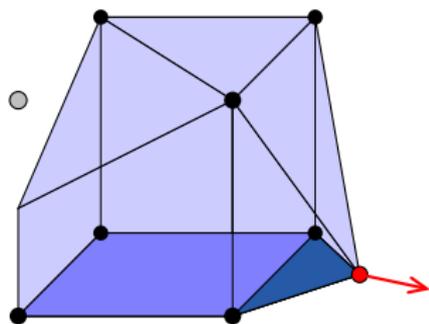
1.  $\bar{x} \leftarrow$  LP optimum;
2. Fix all integral variables:  
 $x_i := \bar{x}_i$  for all  $i : \bar{x}_i \in \mathbb{Z}$ ;
3. Reduce domain of fractional variables:  
 $x_i \in \{\lfloor \bar{x}_i \rfloor; \lceil \bar{x}_i \rceil\}$ ;
4. Solve the resulting sub-MIP



# RENS (Relaxation Enforced Neighborhood Search)

## Algorithm

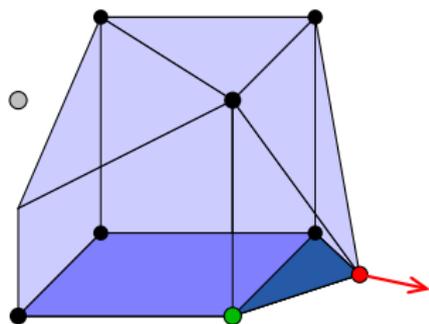
1.  $\bar{x} \leftarrow$  LP optimum;
2. Fix all integral variables:  
 $x_i := \bar{x}_i$  for all  $i : \bar{x}_i \in \mathbb{Z}$ ;
3. Reduce domain of fractional variables:  
 $x_i \in \{ \lfloor \bar{x}_i \rfloor; \lceil \bar{x}_i \rceil \}$ ;
4. Solve the resulting sub-MIP



# RENS (Relaxation Enforced Neighborhood Search)

## Algorithm

1.  $\bar{x} \leftarrow$  LP optimum;
2. Fix all integral variables:  
 $x_i := \bar{x}_i$  for all  $i : \bar{x}_i \in \mathbb{Z}$ ;
3. Reduce domain of fractional variables:  
 $x_i \in \{\lfloor \bar{x}_i \rfloor; \lceil \bar{x}_i \rceil\}$ ;
4. Solve the resulting sub-MIP



# RENS (Relaxation Enforced Neighborhood Search)

## Observations

- ▷ Solutions found by RENS are roundings of  $\bar{x}$
- ▷ Yields best possible rounding
- ▷ Yields certificate, if no rounding exists

## Results

# RENS (Relaxation Enforced Neighborhood Search)

## Observations

- ▷ Solutions found by RENS are roundings of  $\bar{x}$
- ▷ Yields best possible rounding
- ▷ Yields certificate, if no rounding exists

## Results

- ▷ 82 of 129 test instances are roundable
- ▷ RENS finds a global optimum for 23 instances!
- ▷ Dominates all other rounding heuristics

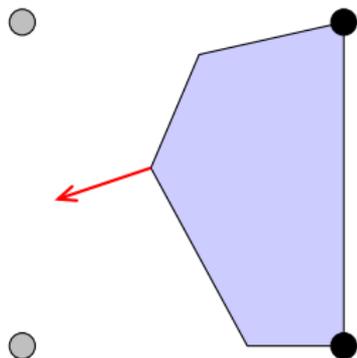
## Approaches

- ▷ **Rounding**: Change fractional to integral values
- ▷ **Diving**: simulate DFS in the branch-and-bound tree using some special branching rule
- ▷ **Objective diving**: manipulate objective function (instead of bounds)
- ▷ **Large Neighborhood Search**: solve some sub-MIP
- ▷ **Pivoting**: manipulate simplex algorithm
- ▷ **Combinatorial**: use special polyhedral properties

# The Feasibility Pump (Fischetti, Lodi et al.)

## Algorithm

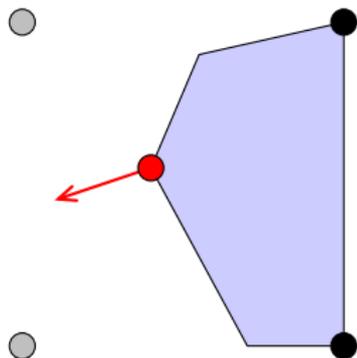
1. Solve LP;
2. Round LP optimum;
3. If feasible:
4.   Stop!
5. Else:
6.   Change objective;
7.   Go to 1;



# The Feasibility Pump (Fischetti, Lodi et al.)

## Algorithm

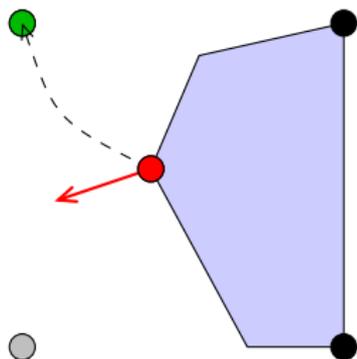
1. Solve LP;
2. Round LP optimum;
3. If feasible:
4. Stop!
5. Else:
6. Change objective;
7. Go to 1;



# The Feasibility Pump (Fischetti, Lodi et al.)

## Algorithm

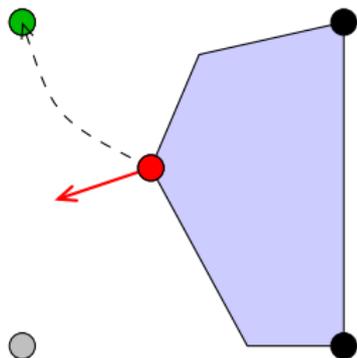
1. Solve LP;
2. Round LP optimum;
3. If feasible:
4. Stop!
5. Else:
6. Change objective;
7. Go to 1;



# The Feasibility Pump (Fischetti, Lodi et al.)

## Algorithm

1. Solve LP;
2. Round LP optimum;
3. **If feasible:**
4. Stop!
5. Else:
6. Change objective;
7. Go to 1;

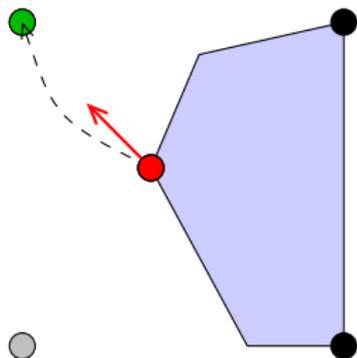


# The Feasibility Pump (Fischetti, Lodi et al.)

## Algorithm

1. Solve LP;
2. Round LP optimum;
3. If feasible:
4. Stop!
5. Else:
6. **Change objective;**
7. Go to 1;

$$\Delta(x, \tilde{x}) = \sum |x_j - \tilde{x}_j|$$

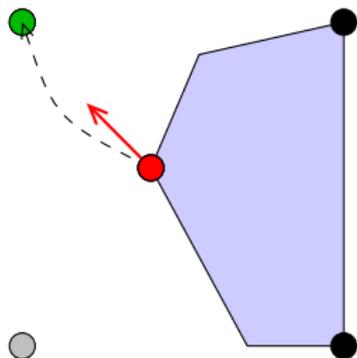


# The Feasibility Pump (Fischetti, Lodi et al.)

## Algorithm

1. Solve LP;
2. Round LP optimum;
3. If feasible:
4.   Stop!
5. Else:
6.   Change objective;
7.   Go to 1;

$$\Delta(x, \tilde{x}) = \sum |x_j - \tilde{x}_j|$$

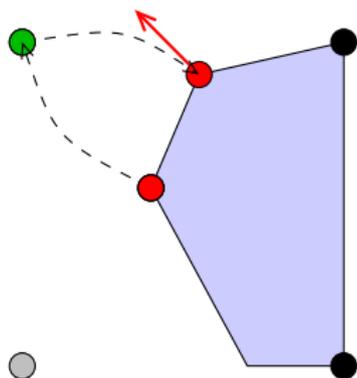


# The Feasibility Pump (Fischetti, Lodi et al.)

## Algorithm

1. Solve LP;
2. Round LP optimum;
3. If feasible:
4. Stop!
5. Else:
6. Change objective;
7. Go to 1;

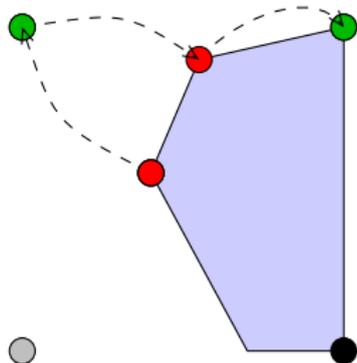
$$\Delta(x, \tilde{x}) = \sum |x_j - \tilde{x}_j|$$



# The Feasibility Pump (Fischetti, Lodi et al.)

## Algorithm

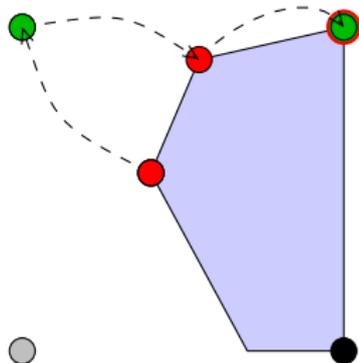
1. Solve LP;
2. Round LP optimum;
3. If feasible:
4. Stop!
5. Else:
6. Change objective;
7. Go to 1;



# The Feasibility Pump (Fischetti, Lodi et al.)

## Algorithm

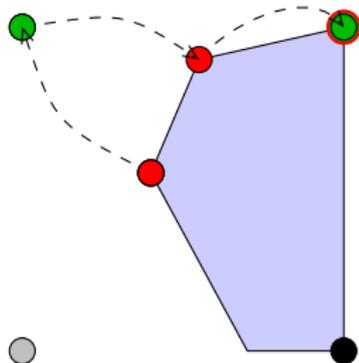
1. Solve LP;
2. Round LP optimum;
3. **If feasible:**
4. Stop!
5. Else:
6. Change objective;
7. Go to 1;



# The Feasibility Pump (Fischetti, Lodi et al.)

## Algorithm

1. Solve LP;
2. Round LP optimum;
3. If feasible:
4. **Stop!**
5. Else:
6. Change objective;
7. Go to 1;



## Improvements

- ▷ Objective  $c^T x$  regarded at each step:  
 $\tilde{\Delta} := (1 - \alpha)\Delta(x) + \alpha c^T x$ , with  $\alpha \in [0, 1]$
- ▷ Algorithm able to recover from cycling
- ▷ Quality of solutions much better

## Results

## Improvements

- ▷ Objective  $c^T x$  regarded at each step:  
 $\tilde{\Delta} := (1 - \alpha)\Delta(x) + \alpha c^T x$ , with  $\alpha \in [0, 1]$
- ▷ Algorithm able to recover from cycling
- ▷ Quality of solutions much better

## Results

- ▷ Finds a solution for 74% of the test instances
- ▷  $\approx 20\%$  more running time
- ▷ Optimality gap decreased from 107% to 38%

## Feasibility Pump 2.0

- ▷ applies propagation after each rounding
- ▷ uses specific propagators for special linear constraints
- ▷ fewer rounding steps, “more feasible”

## Results

# (Objective) Feasibility Pump 2.0 (Fischetti & Salvagnin)

## Feasibility Pump 2.0

- ▷ applies propagation after each rounding
- ▷ uses specific propagators for special linear constraints
- ▷ fewer rounding steps, “more feasible”

## Results

- ▷ fewer ( $\approx 50\%$ ) iterations, hence
- ▷ better quality, higher success rate
- ▷ benefits combine with Objective FP improvements

# SCIP primal heuristics



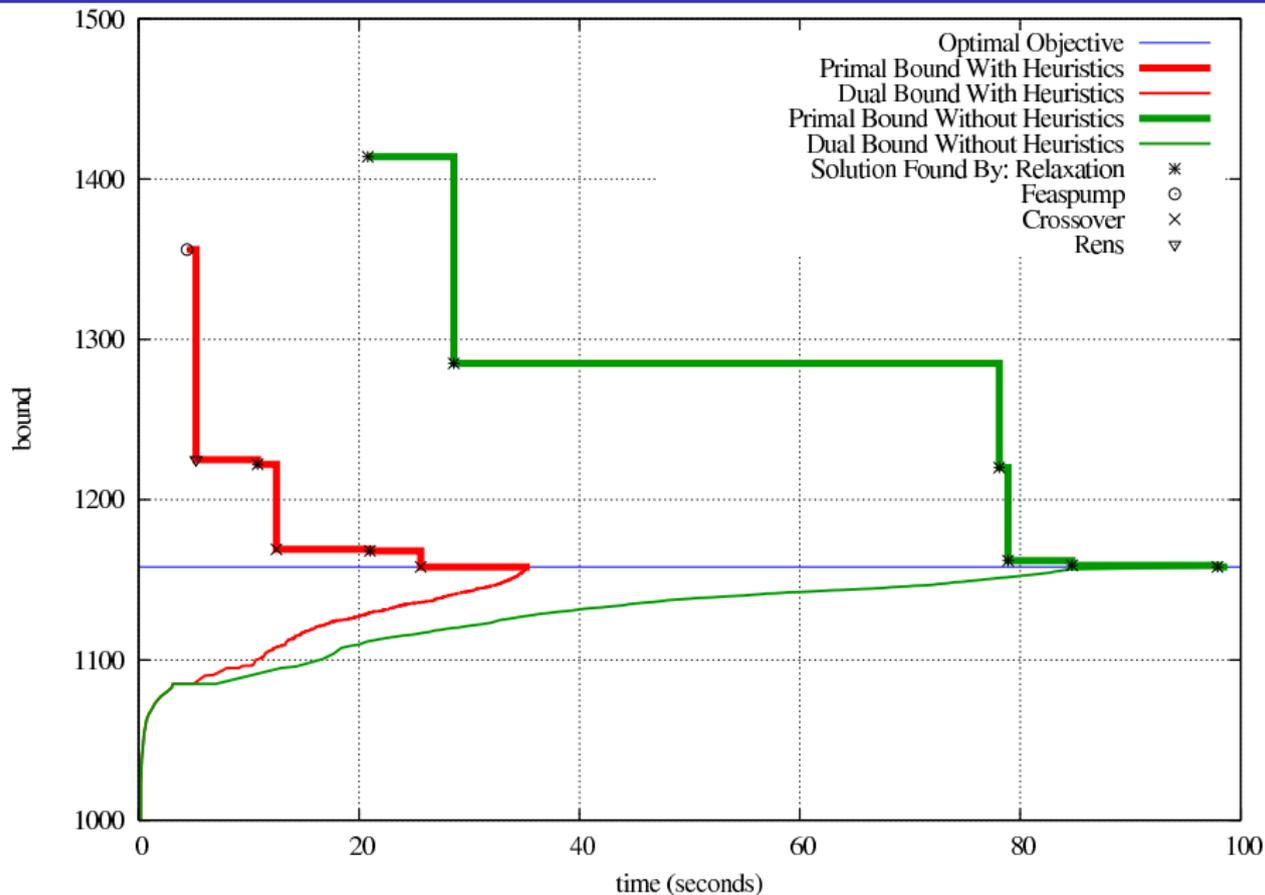
## By approach

- ▷ 8 Diving heuristics
- ▷ 6 LNS heuristics
- ▷ 4 Rounding heuristics
- ▷ 4 Combinatorial / Others
- ▷ 3 Objective divers
- ▷ 2 Problem specific

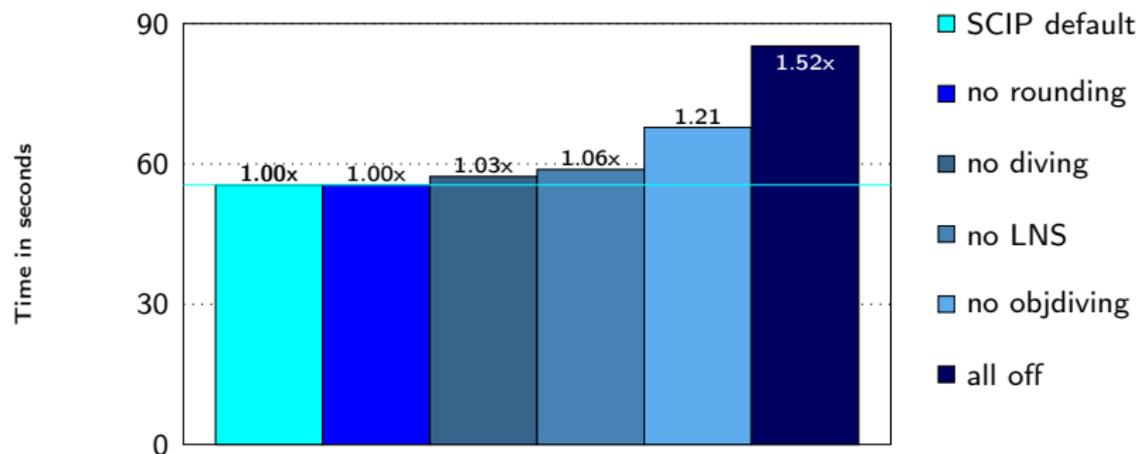
## By category

- ▷ 25 start heuristics
- ▷ 6 improvement heuristics
- ▷ 2 repair heuristics

# An Example



# Impact of Different Heuristics



- ▷ Results for SCIP version 1.1
- ▷ Default settings ↔ disabling classes of heuristics
- ▷ 35 Instances from MIPLIB2003 which SCIP solves within 1 hour

## Single Heuristics

- ▷ Deactivating a single heuristic yields 1%-6% degradation
- ▷ No heuristic clearly dominating (best one: objective feaspump)
- ▷ Coordination important

## Overall Effect

- ▷ Better pruning, earlier fixing
- ▷ 7% less instances without any solution
- ▷ 5% more instances solved within one hour
- ▷ Only half of the branch-and-bound-nodes
- ▷ Only 70% of the solving time

# Cutting Planes and Primal Heuristics

CO@Work Berlin

Timo Berthold and Kati Wolter

09/30/2009



Berlin  
Mathematical  
School



**DFG Research Center MATHEON**  
Mathematics for key technologies



# Once again,...

- ▷ Heuristically build groups of 3 people (e.g., nearest-neighbor)
  - ▶ laptop owner
  - ▶ C expert
  - ▶ IP expert
- ▷ Open your mouth, if you get stuck. ;-)

