# Pseudo Code for Repair Algorithm

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## 1 Input

- A problem  $P^0 = min\{c^Tx \mid Ax \ge b, x_i \in \{0,1\}, \forall i \in \mathcal{I}, \mathcal{I} \subseteq N = \{1,2,\ldots,n\}\}$  with n binary variables x, objective function  $c^Tx$  (min), constraint set  $C^0$  with an optimal solution  $x^0$ .
- A problem  $P^1$  with n binary variables x, objective function cx (min), constraint set  $C^1$ , such that  $C^0 \subseteq C^1$ .

## 2 Output

• An optimal solution  $x^1$  to  $P^1$ .

#### 3 General Idea

We propose to solve  $P^1$  by reusing the optimal solution  $x^0$  to  $P^0$ . In order to achieve this, we define a new problem Q with constraint set  $C^1$  and objective function

$$\min cx + \alpha |x - x^0|,$$

where  $|x - x^0| = \sum_{i=0}^{n-1} |x_i - x_i^0|$ , and  $\alpha$  is a *penalty* term for deviating from the input solution  $x^0$ . This would tentatively help the search for a good solution to  $P^1$ . However, unless  $x^0$  is feasible for  $P^1$ , an optimal solution to Q will in general not be optimal for  $P^1$ .

To remedy thiss problem, we will instead solve a sequence of problems  $Q^0, Q^1, \ldots$ , where the penalty factor  $\alpha$  will gradually decrease until it reaches 0, say at iteration k, in which case  $Q^k = P^1$ . This sequence of problems can be efficiently solved using a technique called *reoptimisation*, which is implemented in the MIP solver SCIP.

#### 4 Pseudo Code

#### **Algorithm 1:** Restriction

```
Data: G = (X, U) such that G^{tc} is an order.
   Result: G' = (X, V) with V \subseteq U such that G'^{tc} is an interval order.
 1 begin
       V \longleftarrow U
 \mathbf{2}
       S \longleftarrow \emptyset
 3
       for x \in X do
 4
           NbSuccInS(x) \longleftarrow 0
           NbPredInMin(x) \longleftarrow 0
 6
           NbPredNotInMin(x) \leftarrow |ImPred(x)|
 7
       end
 8
       for x \in X do
 9
           if NbPredInMin(x) = 0 and NbPredNotInMin(x) = 0 then
10
               AppendToMin(x)
11
           end
12
       \mathbf{end}
13
       while S \neq \emptyset do
14
           remove x from the list of T of maximal index
15
           while |S \cap ImSucc(x)| \neq |S| do
16
               for y \in S - ImSucc(x) do
17
                   { remove from V all the arcs zy : }
18
                   for z \in ImPred(y) \cap Min do
19
                       remove the arc zy from V
20
                       NbSuccInS(z) \longleftarrow NbSuccInS(z) - 1
\mathbf{21}
                       move z in T to the list preceding its present list
22
                       {i.e. If z \in T[k], move z from T[k] to T[k-1]}
\mathbf{23}
                   end
\mathbf{24}
                   NbPredInMin(y) \longleftarrow 0
25
                   NbPredNotInMin(y) \longleftarrow 0
26
                   S \longleftarrow S - \{y\}
27
                   AppendToMin(y)
\mathbf{28}
               end
29
           end
30
           RemoveFromMin(x)
31
32
       end
33 end
```

#### Algorithm 2: How to write algorithms

```
Result: Write here the result
1 initialization;
2 while While condition do
      instructions;
 3
      if condition then
 4
          instructions1;
 5
          instructions2;
 6
      else
 7
          instructions3;
 8
      end
 9
10 end
```

#### 5 MIP

#### 5.1 Mixed Integer Programming

**Definition 5.1.** (Mixed Integer Programming)

Let  $m, n \in \mathbb{N}$ , The given matrix  $A \in \mathbb{R}^{m \times n}$ , vectors  $b \in \mathbb{R}^m$ , and the vector  $c \in \mathbb{R}^n$ , and a set  $\mathcal{I} \subseteq N = \{1, \ldots, n\}$ . the problem

(MIP) 
$$c^* = \min c^T x$$
$$s.t. \quad Ax \ge b$$
$$x_i \in \mathbb{Z}_{\ge 0} \quad \forall_i \in \mathcal{I}$$
$$x_j \in \mathbb{R}_{>0} \quad \forall_i \in \mathcal{N} \setminus \mathcal{I}$$

is called mixedinteger program with the objective function  $c^T x$  and constraints  $A_i x \geq b_i$  for all i = 1, ..., m.

A vector  $x \in X_{MIP} = \{x \in \mathbb{R}_{\geq 0}^n \mid A_x \geq b, x_i \in \mathbb{Z}_{\geq 0} \ \forall i \in \mathcal{I} \}$  is called *feasiable solution* and  $X_{MIP}$  the set of feasible solutions. A feasible  $x^*$  is called optimal, if  $x^*$  satisfies  $c^* = c^T x^*$ .

Common special cases of MIPs are linear programs (LPs) for  $\mathcal{I} = \emptyset$  and integer program (IPs) for  $\mathcal{I} = N$ . Additional, an integer variable bounded by 0 and 1 is called binary variable. let  $\mathcal{B} \subset \mathcal{I}$  denote the set of binary variables. An integer program with  $\mathcal{B} = N$  is called binary program (BP) or mixed binary program (MBP), if  $\mathcal{B} = \mathcal{I} \subsetneq N$ .

A lower or dual bound on a MIP can be computed by neglecting the intergrality constraints. the so-obtained problem is called the LP-relaxation of the MIP.

**Definition 5.2.** (LP-relaxation)

Given a MIP as introduced in Definition 5.1. The LP-relaxation is defined as

(MIP) 
$$c^* = \min c^T x$$
  
 $s.t. \quad Ax \ge b$   
 $x \in \mathbb{R}^n_{>0}$ 

Analogous to  $X_{MIP}$  we can define  $X_{LP}$  as the set of feasible solutions of the LP-relaxation. A feasible solution  $x_{LP}^* \in X_{LP}$  is called LP-optimal if  $c_{LP}^* = c^T x_{LP}^*$ . In general solving MIPs is NP-hard. One common method for solving MIPs is LP-basedbranch – and – bound. This method splits the problem into smaller subproblems, and procedure is repeated on these subproblems. At any point a global upper or primal bound is given by the best known solution, if existent, and a local lower bound or dual bound is given by the respective LP-relaxation.

#### 5.2 Pseudo-Boolean optimization

In the section 2.4 we will present a special kind of a binary problem, a so-called pseudo-Boolean problem. For this purpose we introduce the basic definition of a pseudo-Boolean problem in this section. For more detail we refer to Hammer and Rubin and Boros and Hammer and the references therein.

Let us denote by  $\mathbb{B} = \{0,1\}$  the set of binary values and let  $N = \{1,\ldots,n\}$  be an index set, Reflecting to Boros and Hammer we consider functions in n binary variables  $x_1, x_2, \ldots, x_n$  and denote the binary vector by  $(x_1, x_2, \ldots, x_n in \mathbb{B}^n)$ . A function  $f : \mathbb{B}^n \to \mathbb{R}$  of the form

$$f(x_1, x_2, \dots, x_n) = \sum_{S \subseteq N} C_S \prod_{i \in S} x_i$$

where  $C_s \in \mathbb{R}$  for each  $S \subseteq N$ , is called pseudo - Boolean function. see e.g., Hannmer et al. The degree of the function deg(f) is given by the seize of the largest set  $S \subseteq N$  which  $C_S \neq 0$ . A pseudo-Boolean function f is called linear, quadratic, cubic etc. if  $deg(f) \leq 1, 2, 3$  etc. repectively. Liu and Truszczynski defined a pseudo - Boolean constraint as an integer inequality of the form

$$\sum_{i=1}^{n} a_i x_i \ge b$$

with  $a_i, bin\mathbb{Z}$  and  $xi \in \mathbb{B}$  for all iin[n]. A binary problem defined by a pseudo-Boolean objective function and a set of pseudo-Boolean constraints is called  $pseudo-Boolean \ optimization \ problem$ .