#### Exercice 1. Alternative systems

**Lemma 1 (Farkas' Lemma)** Let  $A \in \mathbb{R}^{m \times n}$  and  $b \in \mathbb{R}^m$ . The linear system :

$$Ax = b$$

$$x \ge 0$$

has a solution if and only if  $y^{\top}b \geq 0$  for all  $y \in \mathbb{R}^m$  such that  $y^{\top}A \geq 0$ .

Theorem 1 (Fredholm's theorem) Let  $A \in \mathbb{R}^{m \times n}$  and  $b \in \mathbb{R}^m$ . The linear system :

$$Ax = b$$

has a solution if and only if  $y^{\top}b = 0$  for all  $y \in \mathbb{R}^m$  such that  $y^{\top}A = 0$ .

Question 1. Prove Farkas's lemma using linear programming duality.

Question 2. Prove Fredholm's alternatives theorem using Farkas' lemma.

### Exercice 2. Benders' reformulation

Consider the following mixed-integer linear program:

$$\min_{x \in \mathbb{Z}_{+}^{n_{x}}, y \in \mathbb{R}_{+}^{n_{y}}} c^{\top} x + f^{\top} y$$
s.t. 
$$Tx + Wy \ge h$$

Show that this problem can equivalently be written as:

$$\min_{x \in \mathbb{Z}_{+}^{n_{x}}, \theta \in \mathbb{R}} c^{\top} x + \theta$$
s.t.  $\theta \ge \pi_{i}^{\top} (h - Tx)$   $\pi_{i} \in ext(\Pi)$ 

$$\pi_{i}^{\top} (h - Tx) \le 0$$
  $\pi_{j} \in ray(\Pi)$ 

where  $\Pi = \{\pi \geq 0 \mid \pi^\top W \leq f\}$  and  $ext(\Pi)$  and  $ray(\Pi)$  are, respectively, its extreme points and exreme rays.

**Hint** : Start by writing the problem as  $\min_{x \in \mathbb{Z}_+^{n_x}} c^\top x + Q(x)$  where Q(x) is defined as :

$$Q(x) := \min \quad f^{\top} y$$
 s.t.  $Wy > h - Tx$ 

then use duality theory.

#### Exercice 3. Dual of the shortest path problem

Let G = (V, A) be a directed graph with costs  $c_{ij}$  for  $(i, j) \in A$  and consider the shortest path problem on this graph from  $s \in V$  to  $t \in V$ .

Let  $x_{ij}$  for  $(i, j) \in A$  be decision variables such that  $x_{ij} = 1$  if arc (i, j) is chosen as part of the shortest path and 0 otherwise. A linear programming formulation for this problem can be written as:

$$\min \sum_{(i,j)\in A} c_{ij} x_{ij}$$
s.t. 
$$\sum_{j\in \delta^{-}(i)} x_{ji} - \sum_{j\in \delta^{+}(i)} x_{ij} = d_i \qquad \forall i\in V$$

$$x_{ij} \geq 0 \qquad \forall (i,j)\in A$$

where  $\delta^+(i)/\delta^-(i)$  are, respectively, the forward and backward star of  $j \in V$  and  $d_i = -1$  for i = s and  $d_i = 1$  for i = t and  $d_i = 0$ , otherwise.

Question 1. Write the linear programming dual of this formulation.

# Exercice 4. Branch-and-bound algorithm

Consider the following instance of the (binary) knapsack problem where the knapsack capacity is given as W = 6 and the item profits  $u_i$  and item weights  $w_i$  are summarized in the following table :

Question 1. Apply the branch-and-bound algorithm to this instance :

- Dual bounds can be calculated by solving linear programming relaxations.
- Choice of branching variables and nodes to treat can be done randomly (or according to a rule of your choosing).

## Exercice 5. Lagrangean dual

Consider the following optimization problem:

$$\min_{x \in \{0,1\}^n} c^{\top} x 
\text{s.t.} x \in X 
 a^{\top} x \le b$$
(P)

where X is a given polyhedron.

**Question 1.** Show that the problem :

$$L(\lambda) := \min_{x \in \{0,1\}^n} \quad c^\top x + \lambda (a^\top x - b)$$
s.t.  $x \in X$ 

is a relaxation of (P) for all  $\lambda \geq 0$ .

Question 2. Show that the problem:

$$\max_{\lambda \ge 0} L(\lambda)$$

provides a dual bound on the optimal value of P. (This is called a Lagrangean dual problem.)

**Question 3.** We next propose to show that the Lagrangean dual problem may provide a better dual bound for (P) compared to its continuous (LP) relaxation.

1. Show that for given  $\lambda$ ,  $L(\lambda)$  is equal to the solution of the following optimization problem:

$$\max \quad \theta$$
 s.t.  $\theta \le c^{\top} x^i + \lambda (a^{\top} x^i - b)$   $\forall x^i \in (X \cap \{0, 1\}^n)$ 

- 2. Based on the previous expression provide a linear programming formulation for the Lagrangean dual problem.
- 3. Write the dual of the Lagrangean dual problem written as a linear program. Show that it is equivalent to:

min 
$$c^{\top}x$$
  
s.t.  $x \in \text{conv}(X \cap \{0, 1\}^n)$   
 $a^{\top}x < b$ 

where  $conv(X \cap \{0,1\}^n)$  is the convex hull of all feasible solutions.

4. What can we say about the Lagrangean dual bound compared to the dual bound obtained from:

min 
$$c^{\top}x$$
  
s.t.  $x \in (X \cap [0, 1]^n)$   
 $a^{\top}x \le b$