

ISE 426

Optimization models and applications

Lecture 17 — October 30, 2014

- ▶ “Good” and “bad” formulations
- ▶ Branch&bound for MILP
- ▶ Examples of B&B

Reading:

- ▶ Hillier & Lieberman, Chapter 13, 13.4 to 13.5
- ▶ Winston & Venkataramanan, Chapter 9
- ▶ Winston, Chapter 9

Relaxations and efficiency

Integer programming problems:

$$\begin{aligned} (IP) \quad \min \quad & c_1x_1 + c_2x_2 + \dots + c_nx_n \\ & a_{11}x_1 + a_{12}x_2 + \dots + a_{1n}x_n \leq b_1 \\ & a_{21}x_1 + a_{22}x_2 + \dots + a_{2n}x_n \leq b_2 \\ & \vdots \\ & a_{m1}x_1 + a_{m2}x_2 + \dots + a_{mn}x_n \leq b_m \\ & x_i \in \mathbb{Z} \quad \forall i \in J \subseteq \{1, 2, \dots, n\} \end{aligned}$$

or, for short,

$$\begin{aligned} (IP) \quad \min \quad & c^\top x \\ & Ax \leq b \\ & x_i \in \mathbb{Z} \quad \forall i \in J \subseteq N, \end{aligned}$$

can be solved using their LP relaxation:

$$\begin{aligned} (LP) \quad \min \quad & c^\top x \\ & Ax \leq b. \end{aligned}$$

A global optimum z of (LP) is a **lower bound** for (IP) .

Relaxations and efficiency

If an optimal solution x^* of (LP) is feasible for (IP) , i.e., for all $i \in J$ we have $x_i^* \in \mathbb{Z}$, we're done!

This is **not** the case, usually...

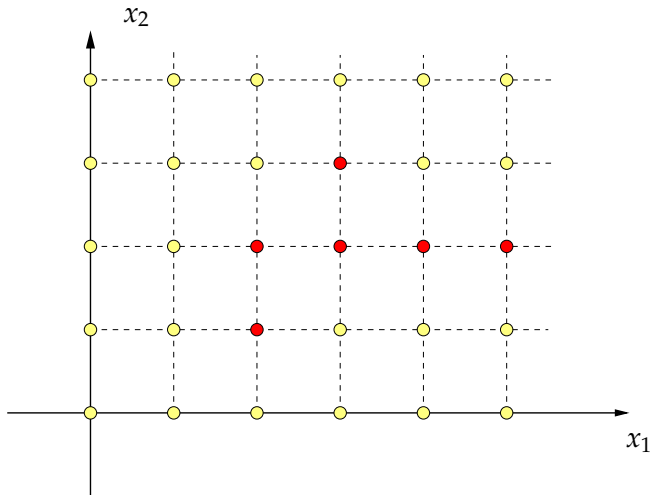
What do we know about the optimal solutions of (LP) ? They are all *vertices* of the polyhedron

$$\{x \in \mathbb{R}^n : A^\top x \leq b\}$$

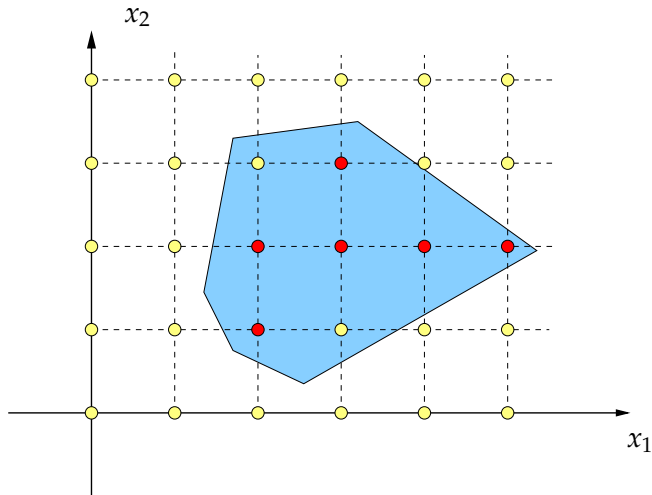
Therefore, it would be just great if all vertices of (LP) were feasible for (IP) . Solving IPs would amount to solving LPs, which are a lot easier.

A good model may not achieve just that, but it can help a lot.

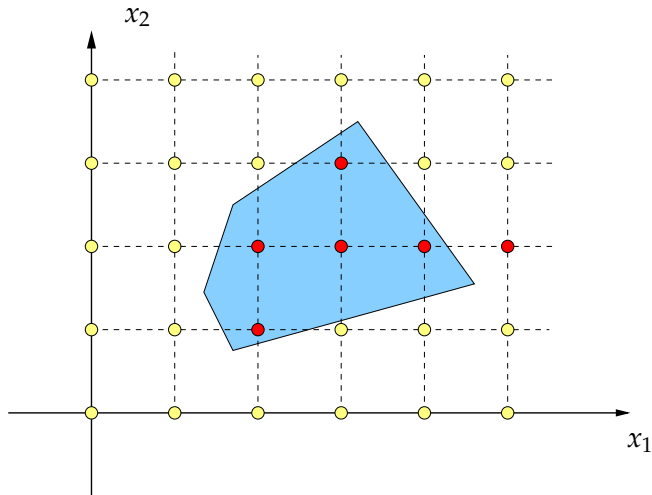
Relaxations, the geometrical standpoint



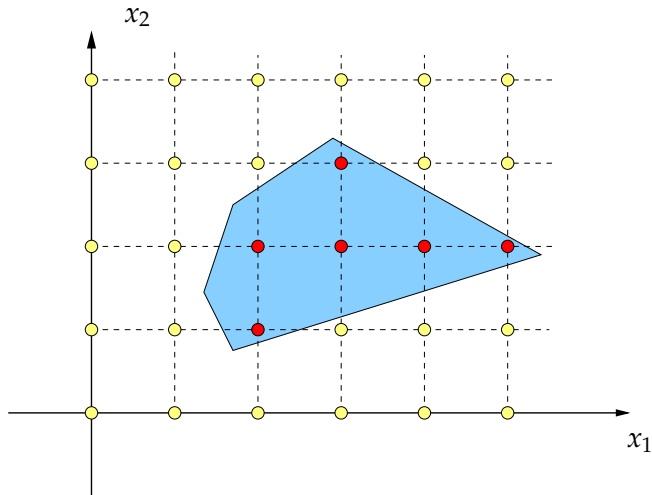
Relaxations, the geometrical standpoint



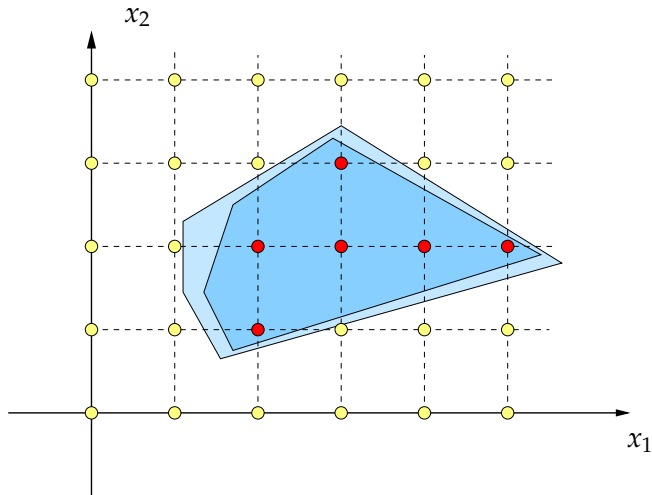
Relaxations, the geometrical standpoint



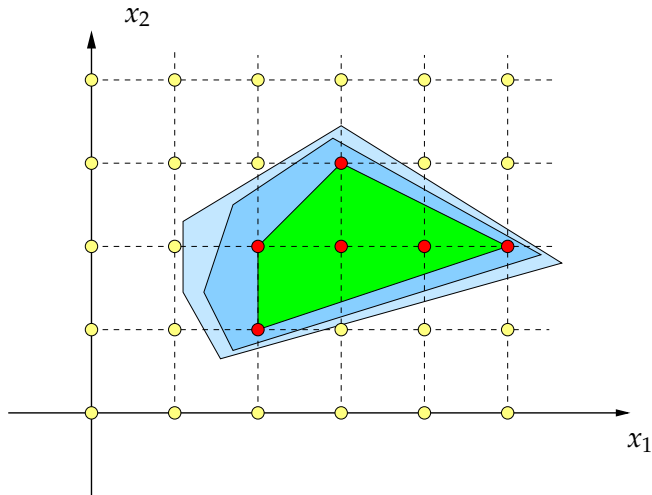
Relaxations, the geometrical standpoint



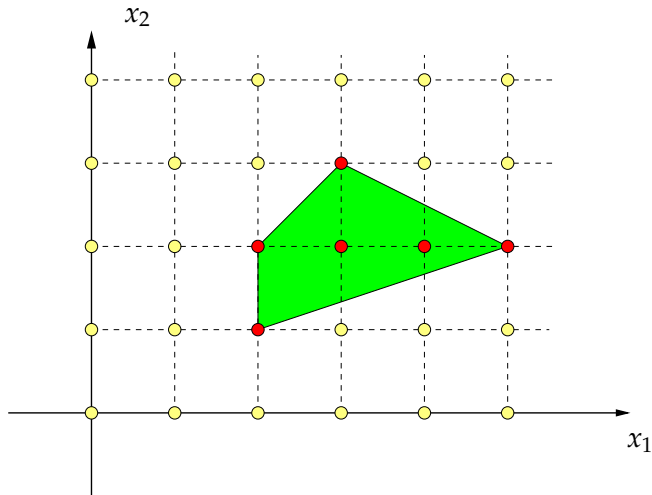
Relaxations, the geometrical standpoint



Relaxations, the geometrical standpoint



Relaxations, the geometrical standpoint



Relaxations: the clique inequality

Two models for one problem have the same feasible set and global optima, but may be solved differently:

$$\left. \begin{array}{ll} P_1 : \min & -7x_1 - 8x_2 - 9x_3 \\ \text{s.t.} & x_1 + x_2 \leq 1 \\ & x_1 + x_3 \leq 1 \\ & x_2 + x_3 \leq 1 \\ & x_1, x_2, x_3 \in \{0, 1\} \end{array} \right\} \equiv \left\{ \begin{array}{ll} P_2 : \min & -7x_1 - 8x_2 - 9x_3 \\ \text{s.t.} & x_1 + x_2 + x_3 \leq 1 \\ & x_1, x_2, x_3 \in \{0, 1\} \end{array} \right.$$

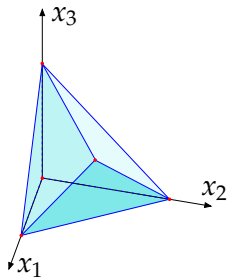
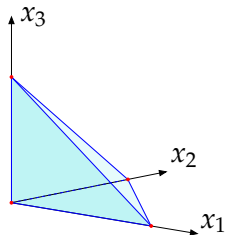
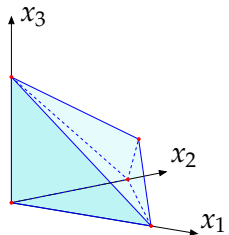
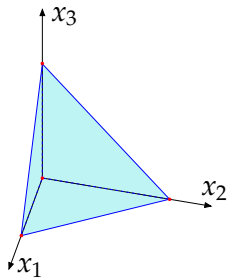
Consider relaxations R_1, R_2 of P_1, P_2 with $x_i \in [0, 1]$.

R_1 : optimal soln. $(\frac{1}{2}, \frac{1}{2}, \frac{1}{2})$, obj.f. -12 : lower bound for P_1, P_2

R_2 : optimal solution $(0, 0, 1)$, obj.f. -9 : lower bound for P_2 and P_1 , and **feasible** for P_2 and P_1 !

\Rightarrow optimum of P_1, P_2 : -9 , and P_2 is a better model than P_1

Relaxations: the clique inequality

 R_1  R_2 

Good vs. bad models: Uncapacitated Facility Location

A set J of retailers has to be served by a set S of plants, **yet to be built**. We don't know where the plants will be, but there is a set I of potential sites, and there is

- ▶ a cost f_i for building plant $i \in I$
- ▶ a (transportation) cost c_{ij} from plant i to retailer j

Each retailer will be served by exactly one plant. Choose a subset S of I such that the total cost is minimized.

Variables:

- ▶ $x_i, i \in I$: 1 if plant i is built, 0 otherwise
- ▶ y_{ij} assigns retailer j to plant i : 1 if i serves retailer j , 0 otherwise

Good vs. bad models: Uncapacitated Facility Location

Objective function:

$$\sum_{i \in I} f_i x_i + \sum_{i \in I} \sum_{j \in J} c_{ij} y_{ij}$$

Constraints:

- ▶ for each customer, one facility: $\sum_{i \in I} y_{ij} = 1$
- ▶ customers go to mall i if it's there:

$$\sum_{j \in J} y_{ij} \leq |J| x_i \quad \forall i \in I$$

or

$$y_{ij} \leq x_i \quad \forall i \in I, j \in J$$

Good vs. bad models: Uncapacitated Facility Location

(A)

$$\begin{aligned} \min \quad & \sum_{i \in I} f_i x_i + \sum_{i \in I} \sum_{j \in J} c_{ij} y_{ij} \\ & \sum_{i \in I} y_{ij} = 1 \quad \forall i \in I \\ & \sum_{j \in J} y_{ij} \leq |J| x_i \quad \forall i \in I \\ & x_i, y_{ij} \in \{0, 1\} \end{aligned}$$

(B)

$$\begin{aligned} \min \quad & \sum_{i \in I} f_i x_i + \sum_{i \in I} \sum_{j \in J} c_{ij} y_{ij} \\ & \sum_{i \in I} y_{ij} = 1 \quad \forall i \in I \\ & y_{ij} \leq x_i \quad \forall i \in I, j \in J \\ & x_i, y_{ij} \in \{0, 1\} \end{aligned}$$

(A) and (B) are **equivalent**. However, for $|I| = |J| = 40$,

(A) takes 14 hours¹

(B) takes 2 seconds

¹On AMPL with an old version of CPLEX.

How do we solve an Integer Programming problem?

$$\begin{aligned}(P) \quad & \min \quad cx \\ & Ax \geq b \\ & x_i \in \mathbb{Z}, i \in J \subseteq \{1, 2, \dots, n\}\end{aligned}$$

- ▶ Relaxing integrality gives an LP problem (easy)
 - ▶ Solving LP gives a **lower bound**
 - ▶ But the solution x^* may have fractional component $x_i^* \notin \mathbb{Z}$, with $i \in J$ (for example, 3.31), infeasible for (P) .
- ⇒ **Divide** the solution set, **partition** the problem into two new **subproblems**, P_1 and P_2 , with

$$P_1 : x_i \leq \lfloor x_i^* \rfloor \quad P_2 : x_i \geq \lceil x_i^* \rceil$$

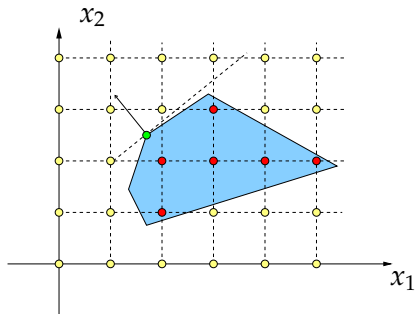
$(P_1 : x_i \leq 3 \text{ and } P_2 : x_i \geq 4)$ and recursively solve P_1 and P_2 .

- ▶ Good: **no** feasible solution of P_1 or P_2 has $x_i = 3.31$

The Branch&Bound - Devide and concour

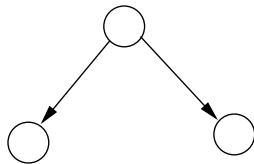
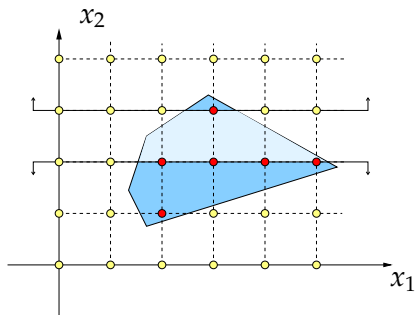
- ▶ If we solve the LP relaxation of P_1 and find a fractional point, we can **recursively** branch on P_1 and obtain two new subproblems P_3 and P_4 .
- ▶ In principle, we have to branch on any node P_k unless its LP relaxation returns a feasible solution or it is infeasible.

Example: minimize $11x_1 - 10x_2$

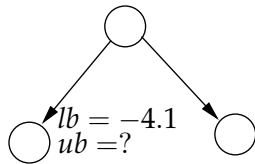
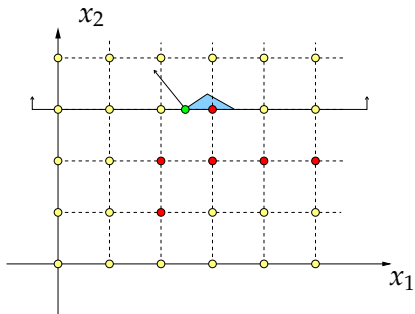


$\bigcirc \begin{matrix} lb = -9.2 \\ ub = ? \end{matrix}$

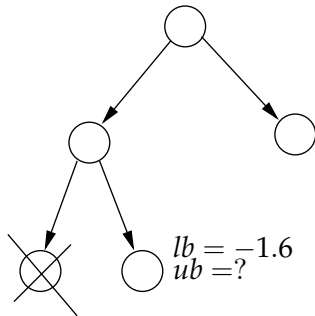
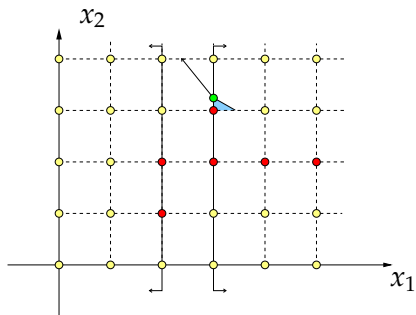
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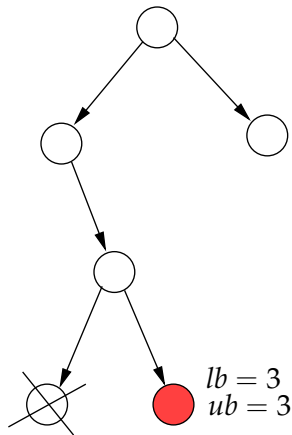
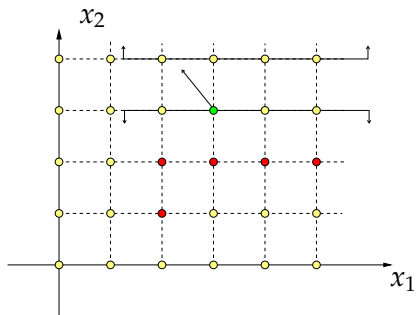
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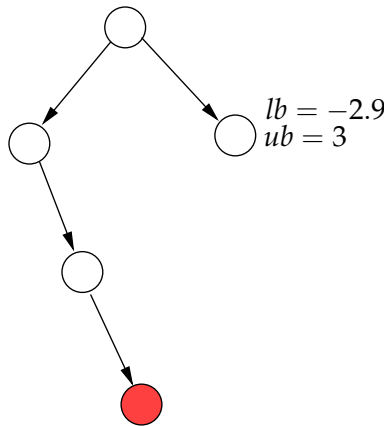
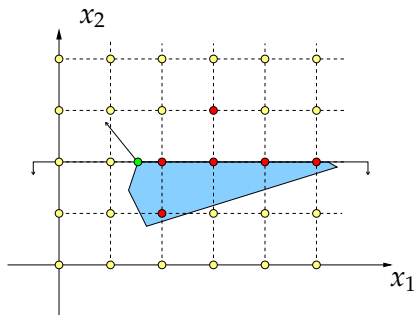
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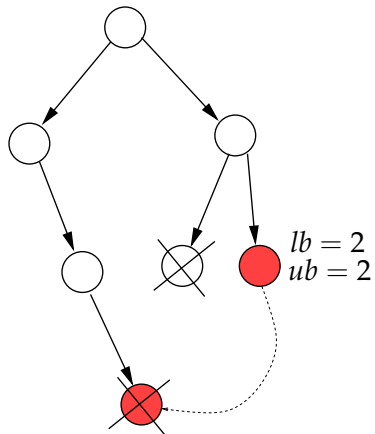
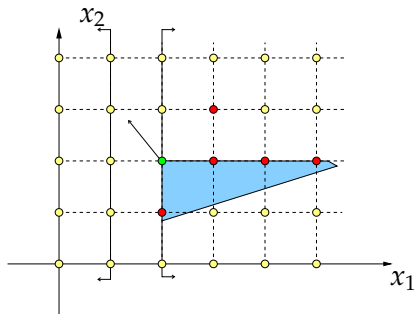
Example: minimize $11x_1 - 10x_2$



Example: minimize $11x_1 - 10x_2$



Example: minimize $11x_1 - 10x_2$



The **Bound** in Branch&Bound

In practice, the **upper bound** is very useful! Suppose you just found an **upper** bound of 194.

- ▶ P_3 has a **lower** bound of 146, P_4 of 203
- ▶ 203 is a lower bound for $P_4 \Rightarrow$ any feasible solution of P_4 has objective function value **worse** than 203 (i.e., ≥ 203)
- ▶ We already have something better (194) \Rightarrow **discard** P_4

How to find upper bounds?

Example: Knapsack problem

$$\begin{array}{rcccccl} \min & 3x_1 & +5x_2 & +8x_3 & +6x_4 & +12x_5 \\ (IP_0) & 10x_1 & +7x_2 & +7x_3 & +5x_4 & +3x_5 & \geq 22 \\ & x_1, & x_2, & x_3, & x_4, & x_5 & \in \{0, 1\} \end{array}$$

The general Knapsack problem is:

$$\begin{array}{ll} \min & \sum_{i=1}^n w_i x_i \\ & \sum_{i=1}^n c_i x_i \geq C \\ & x_i \in \{0, 1\} \quad \forall i = 1, 2, \dots, n \end{array}$$

Suppose that variables are sorted in non-decreasing order w.r.t. weight/value². The LP relaxation is solved as follows:

1. Set $R := C$
2. **for** $i : 1, 2, \dots, n$
3. **if** $c_i \leq R$, **then** $x_i := 1$; $R := R - c_i$
4. **else** $x_i := R/c_i$; **stop**

²Those with a small weight/value ratio are more likely to be chosen.

Solve the LP relaxation

$$\begin{array}{llllll} \min & 3x_1 & +5x_2 & +8x_3 & +6x_4 & +12x_5 \\ (LP_0) & 10x_1 & +7x_2 & +7x_3 & +5x_4 & +3x_5 & \geq 22 \\ & x_1, & x_2, & x_3, & x_4, & x_5 & \in [0, 1] \end{array}$$

- ▶ Solve this by the greedy method.
- ▶ Solution: $x_0^* = (1, 1, \frac{5}{7}, 0, 0)$, $V_0^* = 11\frac{4}{7}$.
- ▶ V_0^* - the lower bound for the problem IP_0 .
- ▶ Split the problem into two cases: $X_3 = 1$ (IP_1) and $X_3 = 0$ (IP_2) and consider the LP relaxations LP_1 and LP_2 .

Consider subproblem

Solve LP_1 problem $X_3 = 1$ (we will consider LP_2 later)

$$\begin{array}{llllll} \min & 3x_1 & +5x_2 & +8 & +6x_4 & +12x_5 \\ (LP_1) & 10x_1 & +7x_2 & +7 & +5x_4 & +3x_5 & \geq 22 \\ & x_1, & x_2, & & x_4, & x_5 & \in [0, 1] \end{array}$$

- ▶ Solve this by the greedy method.
- ▶ Solution: $x_1^* = (1, \frac{5}{7}, 1, 0, 0)$, $V_1^* = 14\frac{4}{7}$.
- ▶ V_1^* - the lower bound for the problem IP_1 .
- ▶ Split the problem into two cases: $X_2 = 1$ and $X_2 = 0$ and consider the LP relaxations LP_3 and LP_4 .

Consider subproblem

Solve LP_3 , $X_2 = 1$, $X_3 = 1$.

$$\begin{array}{llllll} \min & 3x_1 & +5 & +8 & +6x_4 & +12x_5 \\ (LP_1) & 10x_1 & +7 & +7 & +5x_4 & +3x_5 & \geq 22 \\ & x_1, & & & x_4, & x_5 & \in [0, 1] \end{array}$$

- ▶ Solve this by the greedy method.
- ▶ Solution: $x_3^* = (\frac{8}{10}, 1, 1, 0, 0)$, $V_3^* = 15\frac{2}{10}$.
- ▶ V_3^* - the lower bound for the problem IP_3 .
- ▶ Split the problem into two cases: $X_2 = 1$ and $X_2 = 0$ and consider the LP relaxations L_3 and L_4 .

Consider subproblem

Solve LP_3 , $X_2 = 0$, $X_3 = 1$.

$$\begin{array}{rcllcl} \min & 3x_1 & +8 & +6x_4 & +12x_5 \\ (LP_1) & 10x_1 & +7 & +5x_4 & +3x_5 & \geq 22 \\ & x_1, & & x_4, & x_5 & \in [0, 1] \end{array}$$

- ▶ Solve this by the greedy method.
- ▶ Solution: $x_4^* = (1, 0, 1, 1, 0)$, $V_4^* = 17$.
- ▶ V_4^* - the upper bound for the whole IP problem! Also is the optimal solution to IP_4 .

Example: Knapsack problem

Solve LP_2 problem $X_3 = 0$

$$\begin{array}{llllll} \min & 3x_1 & +5x_2 & & +6x_4 & +12x_5 \\ (LP_1) & 10x_1 & +7x_2 & & +5x_4 & +3x_5 & \geq 22 \\ & x_1, & x_2, & & x_4, & x_5 & \in [0, 1] \end{array}$$

- ▶ Solve this by the greedy method.
- ▶ Solution: $x_2^* = (1, 1, 0, 1, 0)$, $V_2^* = 14$.
- ▶ V_2^* is the new upper bound for the entire problem!! Also optimal solution to IP_2 .
- ▶ Key observation: lower bound for IP_3 is bigger than upper bound for the entire problem. DONE!!!!

Branch&Bound

► $z^{\text{ub}} = +\infty$

► $\mathcal{L} \leftarrow \{P\}$

► **while** $\mathcal{L} \neq \emptyset$

 Choose P' from \mathcal{L} and set $\mathcal{L} = \mathcal{L} \setminus \{P'\}$

 Relax $P' \rightarrow$ obtain LP'

 solve LP' , obtain solution $x^{LP'}$ and lower bound $z^{LP'}$

 look for solution feasible for P' , obj. $z^{P'}$

if $z^{P'} < z^{\text{ub}}$, set $z^{\text{ub}} \leftarrow z^{P'}$

if $z^{LP'} < z^{\text{ub}}$ and $x^{LP'}$ infeasible for P

 choose $x_i : x_i^{LP'} \notin \mathbb{Z}$

 create $P'' : x_i \leq \lfloor x_i^{LP'} \rfloor$

 create $P''' : x_i \geq \lceil x_i^{LP'} \rceil$

$\mathcal{L} \leftarrow \mathcal{L} \cup \{P'', P'''\}$