Introduction to Integer Linear Programming, reformulation and decomposition

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Sandra Ulrich Ngueveu CIMPA School 2021: July 6th - 8th, 2021

Université de Toulouse - Toulouse INP - Laboratory LAAS-CNRS ngueveu@laas.fr

Part 3: decomposition methods

Content

Introduction to duality in linear programming

Introduction to column generation and Branch-and-Price

Conclusion and useful references

Introduction to duality in linear programming

$$\max z = 3x_1 + 2x_2 \tag{1}$$

S.C.

- $2x_1 + x_2 \le 18$ (2)
- $2x_1 + 3x_2 \le 42 \tag{3}$
 - $3x_1 + x_2 \le 24 \tag{4}$

$$x_1, x_2 \ge 0 \tag{5}$$

Feasible solutions produce lower bounds for the objective-function value *z*.

• What if we were interested in upper bounds (UB)?

Illustration

$$\max z = 3x_1 + 2x_2 \tag{1}$$

S.C.

 $2x_1 + x_2 \le 18$ (2)

$$2x_1 + 3x_2 \le 42 \tag{3}$$

$$3x_1 + x_2 \le 24 \tag{4}$$

- $x_1, x_2 \ge 0 \tag{5}$
- Multiply constraint (2) by 2 and deduce an UB of z
- Multiply constraint(3) by $\frac{3}{2}$ and deduce an UB of z
- Consider the linear combination (2)+ $\frac{1}{3}$ (3) and deduce an UB of z
- Consider the linear combination $\frac{3}{7}(2) + \frac{3}{7}(3) + \frac{3}{7}(4)$ and deduce an UB of z

S.C.

- $2x_1 + x_2 \le 18$ (2)
- $2x_1 + 3x_2 \le 42 \tag{3}$

$$3x_1 + x_2 \le 24 \tag{4}$$

$$x_1, x_2 \ge 0 \tag{5}$$

- A linear combination produce an UB if and only if each coefficient of a variable is higher or equal to the coefficient of the same variable in the objective-function

Model the problem of finding the best coefficients (linear program)

Exemple

 $\max 3x_1 + 2x_2$ (6)

S.C.

$$2x_1 + x_2 \le 18$$
 (7)

$$2x_1 + 3x_2 \le 42$$
 (8)

 $3x_1 + x_2 \le 24$ (9)

 $x_1, x_2 \ge 0$ (10)

S.C.

 $2u_1 + 2u_2 + 3u_3 \ge 3 \qquad (12)$

 $\min 18u_1 + 42u_2 + 24u_3$

 $u_1 + 3u_2 + u_3 \ge 2$ (13)

$$u_1, u_2, u_3 > 0$$
 (14)

PRIMAL

DUAL

- 1. Solve each of these linear programs
- 2. Compare the optimal costs
- 3. Write the matrix form of these two problems and comment on it

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(11)

Duality is a fundamental concept in linear programming. We can associate to a linear program (PL) its dual (DL) defined as a linear program:

- with a matrix of constraints coefficients A^{T} , with a vector of decision variables u
- a right-hand-side vector *c*, a cost vector *b*,

according to the following conversion table.

(LP)	Primal	Dual	(DL)
$\min z = c.x$	Objective-function (min)	Right-hand-side	$\max w = u.b$
	Right-hand-side	Objective-function (max)	
s. t.	A constraint matrix	A^{T} constraint matrix	s. t.
	Constraint i: ≥	Variable $u_i \ge 0$	
$A.x \leq b$	Constraint i: =	Variable $u_i \in \mathbb{R}$	$u.A^T \leq c$
	Variable $x_j \ge 0$	Constraint <i>j</i> : ≤	
$x \ge 0$	Variable $x_j \in \mathbb{R}$	Constraint j : =	$u \leq 0$

 Table 1: Primal and Dual: rules and examples

(PL) is then called primal and (DL) is its dual problem.

Relation Primal / Dual

There are special connexions between these two problems, including:

- The dual of (DL) is (PL).
- If \bar{x} if a solution of (PL) and \bar{u} is a solution of (DL), then: $\bar{z} = c.\bar{x} \ge \bar{w} = \bar{u}.b$.
- Optimal solutions x* and u^* of (PL) and (DL) share the same cost $z^* = w^*$.
- If solutions of a (PL) and its (DL) share the same cost, then they are optimal
- The reduced cost ${}^1\widetilde{c}_i$ of the variable \overline{x}_i is:

$$\widetilde{c}_j = c_j - \overline{u} A^j \tag{15}$$

Therefore, in the minimisation case, the cost of a feasible (DL) solution is a lower bound for the optimum, whereas the cost of a feasible (PL) solution is an upper bound.

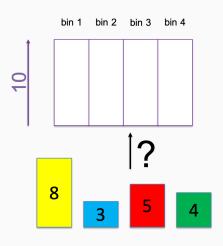
¹The reduced cost of a variable corresponds to the impact on the objective-function value of a unitary incrementation of its current value. At the optimum of a minimisation problem, the reduced cost of all its variables is greater or equal to zero because, if there existed variables with negative reduced cost, that would mean that the values of such variables should have been increased to reduce the objective-function value..

Theorem

If either (PL) or (DL) has a finite optimal solution, then so does the other, and the optimum objective values are equal. It either problem has an unbounded objective value, then the other is infeasible.

Introduction to column generation and Branch-and-Price

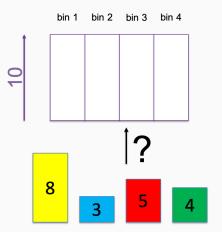
Our case study: the bin packing problem



 $(CF) \min y_1 + y_2 + y_3 + y_4$ s.t.8x_{1,1} + 3x_{1,2} + 5x_{1,3} + x_{1,4} ≤ 10y₁ 8x_{2,1} + 3x_{2,2} + 5x_{2,3} + x_{2,4} ≤ 10y₂ 8x_{3,1} + 3x_{3,2} + 5x_{3,3} + x_{3,4} ≤ 10y₃ 8x_{4,1} + 3x_{4,2} + 5x_{4,3} + x_{4,4} ≤ 10y₄ x_{1,1}, x_{1,2}, x_{1,3}, x_{1,4}, x_{2,1}, x_{2,2}, x_{2,3}, x_{2,4} ∈ {0, 1} x_{4,1}x_{4,2}, x_{4,3}, x_{4,4}, y₁, y₂, y₃, y₄ ∈ {0, 1}

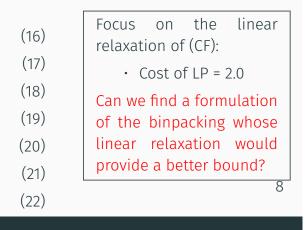
An extended formulation

Key idea: consider as input data all subsets of items that can be stored together



- Data:
 - |J| bins of capacity Q = 10,
 - $\cdot |I| = 4$ items to store,
 - item *i* has a size *w_i*

How to store items in a minimal number of bins whilst respecting the capacity ?



- set of 1 item: 8, 3, 5, 4
- set of 2 items: (3,5), (3,4), (5,4)
- set of 3 items: -
- set of 4 items: -

Which subset of items should we choose for each bin to reduce number of bins used ?

An extended formulation (EF1)

Minimize the number of subset selected

$$\min \sum_{s=1}^{7} \sum_{j=1}^{4} z_{s,j}$$
(23)

s.t.

choose one of the subsets that contain the 1st item

$$z_{1,1} + z_{1,2} + z_{1,3} + z_{1,4} = 1$$
(24)

choose one of the subsets that contain the 2nd item

$$z_{2,1} + z_{2,2} + z_{2,3} + z_{2,4} + z_{5,1} + z_{5,2} + z_{5,3} + z_{5,4} + z_{6,1} + z_{6,2} + z_{6,3} + z_{6,4} = 1$$
(25)

choose one of the subsets that contain the 3rd item

$$z_{3,1} + z_{3,2} + z_{3,3} + z_{3,4} + z_{5,1} + z_{5,2} + z_{5,3} + z_{5,4} + z_{7,1} + z_{7,2} + z_{7,3} + z_{7,4} = 1$$
(26)

choose one of the subsets that contain the 4th item

$$Z_{4,1} + Z_{4,2} + Z_{4,3} + Z_{4,4} + Z_{6,1} + Z_{6,2} + Z_{6,3} + Z_{6,4} + Z_{7,1} + Z_{7,2} + Z_{7,3} + Z_{7,4} = 1$$
(27)

All variables are binary

$$z_{s,j} \in \{0,1\}, \forall s \in \{1,...,7\}, \forall j \in \{1,...,4\}$$
 (28) 10

No need to know which bin was assigned to which subset! (EF2)

Minimize the number of subset selected

$$\min z_1 + z_2 + z_3 + z_4 + z_5 + z_6 + z_7 \tag{29}$$

s.t.

choose one subset that contains the 1st item (8)

$$z_1 = 1$$
 (30)

choose one subset that contains the 2nd item (3)

 $z_2 + z_5 + z_6 = 1 \tag{31}$

choose one subset that contains the 3rd item (5)

$$z_3 + z_5 + z_7 = 1 \tag{32}$$

choose one subset that contains the 4th item (4)

$$z_4 + z_6 + z_7 = 1 \tag{33}$$

All variables are binary

$$z_s \in \{0, 1\}, \forall s \in \{1, ..., 7\}$$
 (34) 1²

Quality of the linear relaxation of (EF2)

Let (LEF2) be the linear relaxation of (EF2). Its optimal solution is :

- $z_1 = 1$
- $z_5 = z_6 = z_7 = 0.5$
- $z_2 = z_3 = z_4 = 0$

which corresponds to an objective-function value of 2,5 !

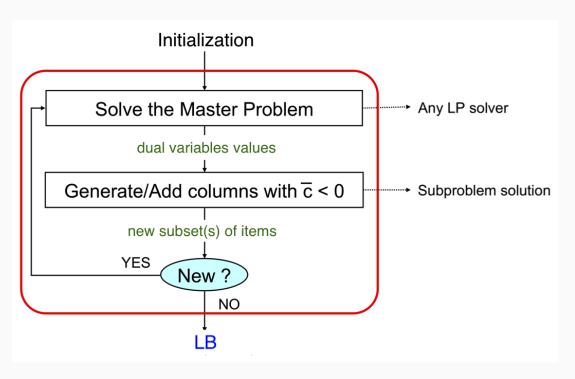
Therefore

- strength of (LEF2): bounds obtained of better quality than (LCF)
- limit of (LEF2): exponential number of variables: for larger instances, it would not be possible to generate (EF2) and feed it to a black-box MILP solver

Key observation: many variables are inactive (set to 0) in the optimal solution of (LEF2).

Column generation

If we could generate only the "good" subset of variables, we could solve (LEF2) without needing to explicitely integrate all the exponential number of variables(=columns)



PRIMAL

$$\min \sum_{s \in \mathcal{S}} Z_s \tag{35}$$

s.t.
$$\sum_{s \in S} a_{i,s} z_s = 1, \quad \forall i \in \{\mathcal{I}\}$$
 (36)

$$z_{s} \geq 0, \qquad \forall s \in \mathcal{S} \quad (37)$$

= master problem

DUAL

$$\max \sum_{i \in \mathcal{I}} u_i \tag{38}$$

s.t.
$$\sum_{i \in \mathcal{I}} a_{i,s} u_i \leq 1, \quad \forall s \in \{\mathcal{S}\}$$
 (39)

$$u_i \in \mathbb{R}, \qquad \forall i \in \mathcal{I}$$
 (40)

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How to identify promising columns

PRIMAL

$$\min \sum_{s \in S} Z_s \tag{35}$$

s.t.
$$\sum_{s \in S} a_{i,s} z_s = 1$$
, $\forall i \in \{\mathcal{I}\}$ (36)
 $z_s \ge 0$, $\forall s \in S$ (37)

DUAL

$$\max \sum_{i \in \mathcal{I}} u_i \tag{38}$$

s.t.
$$\sum_{i \in \mathcal{T}} a_{i,s} u_i \leq 1, \quad \forall s \in \{\mathcal{S}\}$$
 (39)

$$u_i \in \mathbb{R}, \qquad \forall i \in \mathcal{I}$$
 (40)

- = master problem (MP)
 - A restricted master problem (RMP) is obtained if ${\cal S}$ is restricted to a subset $\overline{{\cal S}}$
 - Any column from $S \setminus \overline{S}$ corresponds to a constraint missing from the dual
 - A constraint missing from the dual, but respected by the current solution, can be disregarded because adding it to \overline{S} would not have changed the solution
 - given the current (RMP) solution and the resulting dual variable values \overline{u}_i , is
 - there a missing subset of items that would lead to a violated constraint (39)?
 - \cdot if yes, some of them should be added to $\overline{\mathcal{S}}$ before (RMP) is solved again
 - if no, stop: the current solution of (RMP) is also optimal for (MP)

Objective:

• Given the dual variables values \overline{u}_i corresponding to your current solution, find the subset of items s* and therefore the associated coefficients a_{i,s^*} such that $\sum_{i \in \mathcal{I}} a_{i,s^*} \overline{u}_i > 1$.

Finding this set **s*** consists in solving the following subproblem

$$\max \sum_{i \in \mathcal{T}} \overline{u}_i \alpha_i \tag{41}$$

s.t.
$$\sum_{i\in\mathcal{T}} W_i \alpha_i \le Q$$
 (42)

$$\alpha_i \in \{0, 1\}, \qquad \forall i \in \mathcal{I}$$
(43)

 \Rightarrow a Knapsack problem !

Resulting subproblem

Objective:

• Given the dual variables values \overline{u}_i corresponding to your current solution, find the subset of items s^* and therefore the associated coefficients a_{i,s^*} such that $\sum_{i \in \mathcal{I}} a_{i,s^*} \overline{u}_i > 1$.

Finding this set **s*** consists in solving the following subproblem

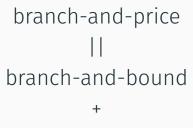
$$\max \sum_{i \in \mathcal{T}} \overline{u}_i \alpha_i \tag{41}$$

s.t.
$$\sum_{i\in\mathcal{I}} w_i \alpha_i \le Q$$
 (42)

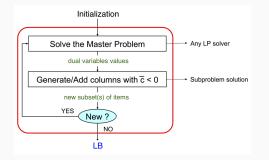
$$\alpha_i \in \{0,1\}, \qquad \forall i \in \mathcal{I}$$
(43)

 \Rightarrow a Knapsack problem !

The resulting column has a reduced cost $\overline{c} = \sum_{i \in \mathcal{I}} \alpha_i \overline{u}_i - 1$



column generation



$$\min \sum_{s \in \mathcal{S}} \sum_{j \in \mathcal{J}} Z_{s,j} \tag{44}$$

s.t.
$$\sum_{j \in \mathcal{J}} x_{i,j} = 1,$$
 $\forall i \in \mathcal{I}$ (45)

$$x_{i,j} = \sum_{s \in S} a_{i,s} z_{s,j}, \quad \forall i \in \mathcal{I}, \forall j \in \mathcal{J}$$
 (46)

$$z_{s,j} \ge 0,$$
 $\forall s \in \mathcal{S}, \forall j \in \mathcal{J}$ (47)

$$x_{i,j} \in \{0,1\}, \quad \forall i \in \mathcal{I}, \forall j \in \mathcal{J}$$
(48)

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Conclusion and useful references

We planned to

- introduce you to the basics of (Mixed) Integer Linear Programming (part 1)
- illustrate how MILP can be used to solve Mixed Integer Nonlinear Problems via piecewise linear approximation (part 2)
- introduce you to principles of the column generation and branch-and-price algorithms (part 3)

With the aim of

• expanding your modeling and solving capabilities

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phpsimplex (educational tool to solve a linear program with simplex or the graphical method): http://www.phpsimplex.com/en/ Thank you for your attention !

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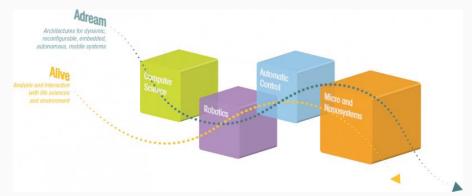


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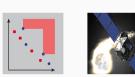
- branches of Operations Research and/or Artificial Intelligence (more specifically Constraint Programming).
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