### Mathematics for Decisions

# Basics of Linear Programming

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#### Overview

Linear Programming

The Simplex method

Graphical method

Duality

Sensitivity analysis

References

Linear Programming

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# **Linear Programming**

A *Linear Programming* (LP) problem is a mathematical programming problem of the form:

$$\begin{array}{ll} \min \ or \ \max \quad c^T x \\ & \text{s.t.} \quad Ax \leq b \\ & x \geq 0 \end{array}$$

where  $x \in \mathbb{R}^n$  are the decision variables,  $b \in \mathbb{R}^m$  is the vector of known values,  $A \in \mathbb{R}^{m \times n}$  and  $c \in \mathbb{R}^n$  is the vector of the coefficients in the objective function.

Linear Programming

#### Canonical and standard form

$$\max c^{T} x$$
s.t.  $Ax \le b$ 

$$x \ge 0$$

$$\max c^{T} x$$
s.t.  $Ax = b$ 

$$x \ge 0$$

Canonical

Standard

The two formulations are equivalent but the conversion from one form to the other may change the number of constraints and variables. Rules to follow:

- Conversion from "min" to "max", changing the sign of  $c^T$
- Constraints conversion from " $\leq$ " to "=", introducing slack variables:  $\mathbf{a}_i^T \mathbf{x} \geq b_i \rightarrow \mathbf{a}_i^T \mathbf{x} + s_i = b_i$ , with  $s_i \geq 0$ ;
- Free variables: if  $x_i$  free, then  $x_i = x_i^+ x_i^-$ , with  $x_i^+, x_i^- \ge 0$ ;

Linear Programming

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# Integer, Mixed Integer and Binary Linear Programming

- Integer LP (ILP): when all variables must assume integer values;
- Mixed Integer LP (MILP): when some variables are integer and other continuous;
- Binary LP (0-1 LP): when all variables can only assume 0 or 1 as values.

# Geometry of Linear Programming

- (Convex) Polyhedron: intersection of a finite number of affine half-spaces and hyperplanes.
- Feasible region: set of feasible solutions  $\mathbf{x} \in \mathbb{R}^n$  that satisfy all the linear inequalities  $\rightarrow$  It's a polyhedron.
- Polytope: a bounded polyhedron.
- Vertex or Extreme point: a point x of a polyhedron P that cannot be expressed as a strict convex combination of other two points of the polyhedron, i.e., there exist no  $\mathbf{y}, \mathbf{z} \in P, \mathbf{y} \neq \mathbf{z}$  and  $\lambda \in (0,1)$  such that  $\mathbf{x} = \lambda \mathbf{y} + (1-\lambda)\mathbf{z}$ .
- Each polyhedron has a finite number of vertices.
- Minkowski-Weyl Theorem: every point of a polytope P can be obtained as a convex combination of its vertices → If the feasible region of a LP is a bounded polytope, then there exists at least one optimal vertex of P.

### Vertices and basic solutions

- The optimal solution of an LP is a vertex: we can start from one vertex arbitrarily and iterate through the vertices, moving to an adjacent one, until the optimal is found.
- Basis of A: a collection of m linearly independent columns of A
- Basic and non-basic variables: x<sub>B</sub> and x<sub>F</sub>

$$A\mathbf{x} = \mathbf{b}$$
 can be written as  $B\mathbf{x}_B + F\mathbf{x}_F = \mathbf{b}$ 

- When  $\mathbf{x}_F = 0$ ,  $\mathbf{x}_B = B^{-1}\mathbf{b}$  is the **basic solution** associated to the basis B. It is:
  - *feasible*, if  $B^{-1}\mathbf{b} \ge 0$ ;
  - degenerate, if  $B^{-1}\mathbf{b}$  has one or more zero components.
- A point x of the polyhedron P := {x ≥ 0 : Ax = b} is a vertex iff x is a basic feasible solution of Ax = b.

# The Simplex method

#### How to solve an LP?

- Enumerate all possible vertices, i.e., all the basic solutions to the problem  $\rightarrow$  Number of vertices  $=\binom{n}{m} = \frac{n!}{m!(n-m)!}$
- Improving this procedure:
  - Verify the optimality of the current solution;
  - Find a way to move from a basic feasible solution to another adjacent with a better value of the objective function.

#### Tableau form:

- Exercise at the blackboard
- See also https://www.youtube.com/watch?v=XK26I9eoS18 and https://www.hec.ca/en/cams/help/topics/The\_ steps\_of\_the\_simplex\_algorithm.pdf

#### Particular cases

- Loop between entering and exiting variables
- Empty feasible region
- Unlimited solution
- Multiple optimal solutions

### Exam 31/07/2017 - Ex. 7

Consider the following LP problem:

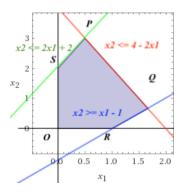
$$\max 3x_1 + 2x_2 2x_1 + x_2 \le 4 -2x_1 + x_2 \le 2 x_1 - x_2 \le 1 x_1, x_2 \ge 0.$$

1. Solve it with the graphical method, specifying the objective function and the variables values at optimum.

Note: the problem is presented in the canonical form, not the standard one.

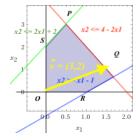
# Graphical method (I)

We represent the three constraints in the plane  $(x_1, x_2)$  obtaining through their intersection the feasible region:



# Graphical method (II)

- The feasible region has five vertices:
  - $0 = x_1 > 0 \cap x_2 >= 0$ :
  - $P = cons_1 \cap cons_2$ ;
  - $Q = cons_1 \cap cons_3$ ;
  - $R = cons_3 \cap x_1 > 0$ ;
  - $S = cons_2 \cap x_2 > 0$ .
- The objective function can be seen as a family of straight lines moving towards the direction where the function is maximized: (3, 2)



# Graphical method (III)

- The optimal solution is given by point  $P = (\frac{1}{2}, 3)$ , the last vertex reached by the family of straight lines;
- Here, the objective function is  $\frac{15}{2}$ .

# Vertices, variables and basic solutions, non-basic variables, ...

- Given a system of linear constraints in *n* variables, we call **solution** a point  $x \in \mathbb{R}^n$  that satisfies all the constraints;
- We write the problem in the standard form, introducing the three slack variables  $s_1, s_2 \in s_3$ :

max 
$$3x_1 + 2x_2$$
  
s.t.  $2x_1 + x_2 + s_1 = 4$   
 $-2x_1 + x_2 + s_2 = 2$   
 $x_1 - x_2 + s_3 = 1$   
 $x_1, x_2 \ge 0$   
 $s_1, s_2, s_3 \ge 0$ 

### Associated bases

2. Determine the bases associated to the vertices of the feasible region;

We can rewrite Ax = b as  $(B|N) \cdot (x_B|x_N)^T = b$  where:

- $B = \text{basic matrix } (m \times m, \text{ composed of } m \text{ columns of A})$
- *N* = non-basic matrix
- $x_B = \text{basic variables}$
- $x_N = \text{non-basic variables}$

# Simplex

3. Specify the sequence of the bases visited by the Simplex method to reach the optimal solution (choose  $x_1$  as the first entering variable);

### Reduced costs

- 4. Determine the values of the reduced costs related to the basic solutions associated to the following vertices, expressed as intersections of straight lines in  $\mathbb{R}^2$ :
  - Eq.-Constraint 1 ∩ Eq.-Constraint 2
  - Eq.-Constraint 1 ∩ Eq.-Constraint 3

### Opposite direction of the gradient vector

5. Verify that the opposite direction of the gradient vector can be expressed as a nonnegative linear combination of the gradients for **active** constraints **only** in the optimal vertex (keep in mind that, since it is a maximization problem, constraints have to be expressed with  $\leq$ ; e.g.,  $x_1 \geq 0$  has to be rewritten as  $-x_1 \leq 0$ ).

# **Duality in Linear Programming**

Any **primal** LP in maximization form is associated to a **dual** LP in minimization form:

Primal Problem

opt=max

Constraint i : <= form = form

Variable j:  $x_j >= 0$  $x_i$  urs **Dual Problem** 

opt=min

Variable i :

y<sub>i</sub> >= 0 y<sub>i</sub> urs

Constraint j: >= form

>= 101111 = form

### Duality theorems

Given the primal problem  $P: \max \mathbf{c}^T \mathbf{x} \text{ s.t. } A\mathbf{x} \leq \mathbf{b}, \mathbf{x} \geq 0 \text{ and the dual problem } D: \min \mathbf{b}^T \mathbf{u} \text{ s.t. } A^T \mathbf{u} \geq \mathbf{c}, \mathbf{u} \geq 0$ :

- The dual of the dual problem D is the primal P.
- Weak duality:  $c^T x \leq b^T u$ .
- Strong duality: P has a finite optimal solution iff D has it too and the value of the two objective function is the same → c<sup>T</sup>x = b<sup>T</sup>u.
- Economic interpretation

### Relationships between Primal and Dual

		DUAL		
		FINITE OPTIMAL SOLUTION	UNBOUNDED	INFEASIBLE
PRIMAL	FINITE OPTIMAL SOLUTION	YES	NO	NO
	UNBOUNDED	NO	NO	YES
	INFEASIBLE	NO	YES	YES

# Optimality conditions

Two vectors  $\bar{\mathbf{x}} \in \mathbb{R}^n$  and  $\bar{\mathbf{u}} \in \mathbb{R}^m$  are optimal for the primal problem P and the dual problem D iff the following optimality conditions hold:

- 1.  $A\bar{\mathbf{x}} \geq \mathbf{b}, \bar{\mathbf{x}} \geq 0$  (primal feasibility)
- 2.  $\mathbf{c}^T \geq \bar{\mathbf{u}}^T A, \bar{\mathbf{u}} \geq 0$  (dual feasibility)
- 3.  $\bar{\mathbf{u}}^T(A\bar{\mathbf{x}}-b)=0$  (complementary slackness)
- 4.  $(\mathbf{c}^T \bar{\mathbf{u}}^T A)\bar{\mathbf{x}} = 0$  (complementary slackness)

# Sensitivity analysis

Once we get the optimal solution, are we done?

- We could investigate how much the solution is stable, w.r.t. changes the parameter data;
- Do not forget that we are solving a model of the problem, not the problem itself! Thus the less sensible is the solution, the more reliable is the model;
- Sensitivity analysis: study of perturbations of initial data whereby conditions:
  - $B^{-1}\mathbf{b} \geq 0$  (primal feasibility for  $\bar{\mathbf{x}}$ );
  - $\bar{\mathbf{c}}^T := \mathbf{c}^T \mathbf{c}_B^T B^{-1} A \ge 0^T$  (dual feasibility for  $\bar{\mathbf{u}}$ , where  $\bar{\mathbf{u}}^T := \mathbf{c}_B^T B^{-1}$ ).
- The basis B remains optimal (not the solution x).
- We'll study three cases:
  - Changes in the right-hand sides
  - Changes in the costs of non-basic variables
  - Changes in the costs of basic variables

### Changes in the right-hand sides

We consider a change of  $\Delta \mathbf{b}$ :

- $B^{-1}(\mathbf{b} + \Delta \mathbf{b}) \ge 0$
- $\bar{\mathbf{c}}^T := \mathbf{c}^T \mathbf{c}_B^T B^{-1} A \ge 0^T$  (unchanged).

So basis B remain feasible and optimal iff:

$$B^{-1}\mathbf{b} \geq -B^{-1}\Delta\mathbf{b}$$

The optimal value changes from  $\mathbf{c}_B^T B^{-1} \mathbf{b}$  to  $\mathbf{c}_B^T B^{-1} (\mathbf{b} + \Delta \mathbf{b}) \rightarrow \Delta z := (\mathbf{c}_B^T B^{-1}) \Delta \mathbf{b} = \bar{\mathbf{u}}^T \Delta \mathbf{b}$ 

The dual variables  $\bar{u}_i$ ,  $i=1,\ldots,m$ , measure the **sensitivity** of the optimal value of the objective function w.r.t. changes  $\Delta b_i$  of the right-hand sides.

### Changes in the costs of non-basic variables

Now we consider a change  $\Delta \mathbf{c}_F^T$  and let  $\mathbf{c}$  and  $\widetilde{\mathbf{c}}$  be the reduced cost vectors before and after change  $\Delta \mathbf{c}_F^T$ .

- $B^{-1}\mathbf{b} \ge 0$  (unchanged);
- $\bullet \ \widetilde{\boldsymbol{c}}^T := [\widetilde{\boldsymbol{c}}_B^T, \widetilde{\boldsymbol{c}}_F^T] = [\boldsymbol{0}^T, (\boldsymbol{c}_F^T + \Delta \boldsymbol{c}_F^T) \boldsymbol{c}_B^T B^{-1} F] \geq \boldsymbol{0}^T.$

As before, we want B to remain optimal, and this happens iff:

$$\tilde{\mathbf{c}}^T = \mathbf{c}_F^T - \mathbf{c}_B^T B^{-1} F + \Delta \mathbf{c}_F^T = \bar{\mathbf{c}}_F^T + \Delta \mathbf{c}_F^T \ge 0 \iff \Delta \mathbf{c}_F \ge -\bar{\mathbf{c}}_F.$$

So we obtain n-m inequalities, independent from each other:

$$\Delta c_j \geq -\bar{c}_j, \forall x_j \text{ non-basic}$$

The reduced cost  $\bar{c}_j \geq 0$  can be interpreted as the maximum **decrease** in cost  $c_i$  under which B remains optimal.

### Changes in the costs of basic variables

Finally we consider a change  $\Delta \mathbf{c}_B^T$  and, as before, and let  $\mathbf{c}$  and  $\widetilde{\mathbf{c}}$  be the reduced cost vectors before and after change  $\Delta \mathbf{c}_B^T$ .

- $B^{-1}\mathbf{b} \ge 0$  (unchanged);
- $\widetilde{\mathbf{c}}^T := [\widetilde{\mathbf{c}}_B^T, \widetilde{\mathbf{c}}_F^T] = [0^T, \mathbf{c}_F^T (\mathbf{c}_B^T + \Delta \mathbf{c}_B^T)B^{-1}F] \ge 0^T.$

So *B* remains optimal iff:

$$\widetilde{\mathbf{c}}_F^T := \mathbf{c}_F^T - \mathbf{c}_B^T B^{-1} F - \Delta \mathbf{c}_B^T B^{-1} F \ge \mathbf{0}^T \iff \Delta \mathbf{c}_B^T B^{-1} F \le \overline{\mathbf{c}}_F^T$$

We have obtained a system which defines a polyhedron in  $\mathbb{R}^m$ , whose points correspond to the vectors  $\Delta \mathbf{c}_B$  for which B does not change.

### References

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