## **Discrete Optimization**

#### MA2827

#### Fondements de l'optimisation discrète

https://project.inria.fr/2015ma2827/

Material from P. Van Hentenryck's course

## Outline

- Linear Programming
- Mixed Integer Program
- Examples (TSP, Knapsack)

## What is a linear program?

 $\min c_1 x_1 + \ldots + c_n x_n$ subject to  $a_{11} x_1 + \ldots + a_{1n} x_n \leq b_1$   $\ldots$   $a_{m1} x_1 + \ldots + a_{mn} x_n \leq b_m$   $x_i \geq 0 \quad (1 \leq i \leq n)$ 

# What is a linear program?

 $\min c_1 x_1 + \ldots + c_n x_n$ subject to  $a_{11} x_1 + \ldots + a_{1n} x_n \leq b_1$   $\ldots$   $a_{m1} x_1 + \ldots + a_{mn} x_n \leq b_m$   $x_i \geq 0 \quad (1 \leq i \leq n)$ 

- n variables, m constraints
- Variables are non-negative
- Inequality constraints

# What is a linear program?

• What about maximization?

**- solve**  $\min -(c_1x_1 + \ldots + c_nx_n)$ 

- What if a variable can take negative values? - replace  $x_i$  by  $x_i^+ - x_i^-$
- Equality constraints?

use two inequalities

- Variables taking integer values?
  - mixed integer programming

• First, convex sets



• First, convex sets





Convex combinations

 $\lambda_1 v_1 + \ldots + \lambda_n v_n$  is a convex combination of  $v_1, \ldots, v_n$  if  $\lambda_1 + \ldots + \lambda_n = 1$ 

and

 $\lambda_i \ge 0 \quad (1 \le i \le n).$ 

- Convex sets
  - A set S in R<sup>n</sup> is convex if it contains all the convex combinations of the points in S
- The intersection of convex sets is convex
  - Proof?

• A half space is a convex set

$$a_1x_1 + \ldots + a_nx_n \le b$$

• Polyhedron: intersection of set of half spaces (also convex). If finite, polytope

$$a_{11}x_1 + \ldots + a_{1n}x_n \le b_1$$
  
$$\ldots$$
  
$$a_{m1}x_1 + \ldots + a_{mn}x_n \le b_m$$















$-4.0x_1$	+	$2.5x_{2}$	$\leq$	-0.25
$-3.0x_{1}$	—	$6.0x_2$	$\leq$	-43.50
$1.5x_{1}$	—	$4.5x_{2}$	$\leq$	3.00
$1.7x_{1}$	—	$1.7x_2$	$\leq$	16.67
$4.8x_{1}$	+	$1.2x_2$	$\leq$	82.33
$2.0x_{1}$	+	$3.5x_{2}$	$\leq$	65.75
$-3.0x_1$	+	$5.0x_2$	$\leq$	29.50

















Every point in a polytope is a convex combination of its vertices











$$\min c_1 x_1 + \ldots + c_n x_n$$
  
subject to  
$$a_{11} x_1 + \ldots + a_{1n} x_n \le b_1$$
  
$$\ldots$$
$$a_{m1} x_1 + \ldots + a_{mn} x_n \le b_m$$
$$x_i \ge 0 \quad (1 \le i \le n)$$

Theorem: At least one of the points where the objective value is minimal is a vertex.









 $\min c_1 x_1 + \ldots + c_n x_n = b$


 $\min c_1 x_1 + \ldots + c_n x_n = b$ 











• Theorem: At least one of the points where the objective value is minimal is a vertex

• Proof ?

Let  $x^*$  be the minimum. Since each point in a polytope is a convex combination of the vertices  $v_1, \ldots, v_t$ , we have

$$x^* = \lambda_1 v_1 + \ldots + \lambda_t v_t$$

and the objective value at optimality can be expressed as

$$cx^* = \lambda_1 * (cv_1) + \ldots + \lambda_t (cv_t).$$

Assume that the minimum is not at a vertex, i.e.,

$$cx^* < cv_i \quad \forall i : 1 \le i \le t.$$

It follows that

$$cx^* = \lambda_1 * (cv_1) + \ldots + \lambda_t (cv_t)$$
  
>  $\lambda_1 * (cx^*) + \ldots + \lambda_t (cx^*)$   
>  $(\lambda_1 + \ldots + \lambda_t)(cx^*)$   
>  $cx^*.$ 

Hence, it must be the case that  $x^* = v_i$  for some  $1 \le i \le t$ .

- How to solve a linear program?
  - Enumerate all the vertices
  - Select the one with the smallest objective value

# Algebraic view

- The simplex algorithm
  - A more intelligent way of exploring the vertices
- Invented by G. Dantzig
- Exponential worst-case, but works well in practice

- Outline
  - 1. An optimal solution is at a vertex
  - 2. A vertex is a basic feasible solution (BFS)
  - 3. You can move from one BFS to a neighboring BFS
  - 4. You can detect whether a BFS is optimal
  - 5. From any BFS, you can move to a BFS with better a cost

$$\min c_1 x_1 + \ldots + c_n x_n$$
  
subject to  
$$a_{11} x_1 + \ldots + a_{1n} x_n \le b_1$$
  
$$\ldots$$
$$a_{m1} x_1 + \ldots + a_{mn} x_n \le b_m$$
$$x_i \ge 0 \quad (1 \le i \le n)$$

Goal: How to find solutions to linear systems

$$\mathbf{a}_{11}x_1 + \ldots + a_{1n}x_n = b_1$$

$$a_{m1}x_1 + \ldots + a_{mn}x_n = b_m$$

$$x_i \ge 0 \quad (1 \le i \le n)$$











Goal: How to find solutions to linear systems

$$\mathbf{a}_{11}x_1 + \ldots + a_{1n}x_n = b_1$$

• • •

$$a_{m1}x_1 + \ldots + a_{mn}x_n = b_m$$

$$x_i \ge 0 \quad (1 \le i \le n)$$





Feasible if  $\forall i \in 1..m : b_i \ge 0$ 

• Select m variables

- Will be the basic variables

• Re-write them using only non-basic variables

- Gaussian elimination

• If all the b's are non-negative

– We have a BFS

• But we do not have equalities

. . .

$$a_{11} x_1 + \ldots + a_{1n} x_n \le b_1$$

$$a_{m1}x_1 + \ldots + a_{mn}x_n \le b_m$$

• But we do not have equalities

$$a_{11} x_1 + \ldots + a_{1n} x_n \leq b_1$$

$$\ldots$$

$$a_{m1}x_1 + \ldots + a_{mn}x_n \leq b_m$$

$$a_{11} x_1 + \ldots + a_{1n} x_n + s_1 = b_1$$

$$\ldots$$

$$a_{m1}x_1 + \ldots + a_{mn}x_n + s_n = b_m$$

$$s_1, \ldots, s_m \geq 0$$
Slack variables

• Re-write the constraints as equalities

With slack variables

• Select m variables

- Will be the basic variables

• Re-write them using only non-basic variables

- Gaussian elimination

• If all the b's are non-negative

– We have a BFS

# Naïve algorithm

- Generate all basic feasible solutions
  - i.e., select m basic variables, perform Gaussian elim.
  - test whether it is feasible
- Select the BFS with the best cost

• But, 
$$\frac{n!}{m!(n-m)!}$$

Can we explore this space more efficiently?

- Outline
  - 1. An optimal solution is at a vertex
  - 2. A vertex is a basic feasible solution (BFS)

#### 3. You can move from one BFS to a neighboring BFS

- 4. You can detect whether a BFS is optimal
- 5. From any BFS, you can move to a BFS with better a cost

- Local search algorithm
- Move from BFS to BFS
- Guaranteed to find a global optimum

– Due to convexity

Key idea: How do we do this move operation?



$x_3$	=	1	_	$3x_1$	_	$2x_2$		
$x_4$	=	2	—	$2x_1$			+	$x_6$
$x_5$	=	3	—	$x_1$			+	$x_6$

- Move to another BFS (local search)
  - Select a non-basic variable with negative coeff.
     (entering variable)
  - Replace a basic variable with this selection (leaving variable)
  - Perform Gaussian elimination









Not a BFS: I cannot select the leaving variable arbitrarily!

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-we must maintain feasibility

$$l = \underset{i:a_{ie} < 0}{\operatorname{arg-min}} \frac{b_i}{-a_{ie}}$$


Move to another BFS:

• Select the entering variable  $x_e$ 

– Non-basic variable with negative coeff.

- Select the leaving variable *x*<sub>l</sub> to maintain feasibility
- Apply Gaussian elimination
  - i.e., eliminate  $x_e$  from the the right hand side
- Pivot(e,l)

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• A BFS is optimal if the objective function, after eliminating all the basic variables is

 $c_0 + c_1 x_1 + \ldots + c_n x_n$ 

 $c_i \ge 0 \ (1 \le i \le n).$ 

• Example

#### • Example

min  $+ x_2 + x_3 + x_4 + x_5$  $x_1$ subject to  $3x_1 + 2x_2 + x_3$ 1  $5x_1 + x_2 + x_3 + x_4$ = 3 $2x_1 + 5x_2 + x_3$ 4 + $x_5$  $3x_1$ min 6  $3x_2$ \_\_\_ \_\_\_\_ subject to  $x_3 = 1 - 3x_1$  $2x_2$ \_\_\_  $x_4 = 2 - 2x_1$ + $x_2$  $x_5 = 3 + x_1$ \_\_\_  $3x_2$ 

$\min$			6	—	$3x_1$	—	$3x_2$
subject to							
	$x_3$	=	1	_	$3x_1$	_	$2x_2$
			0		0		

$x_4$	=	2		$2x_1$	+	$x_2$
$x_5$	—	3	+	$x_1$		$3x_2$

min			6		$3x_1$	—	$3x_2$
subject to							
	$x_3$	=	1	—	$3x_1$	—	$2x_2$
	$x_4$	=	2	_	$2x_1$	+	$x_2$
	$x_5$	=	3	+	$x_1$	_	$3x_2$

min subject to			6	_	$3x_1$	_	$3x_2$
	$x_3$	=	1	—	$3x_1$	—	$2x_2$
	$x_4$	=	2	_	$2x_1$	+	$x_2$
	$x_5$	=	3	+	$x_1$	_	$3x_2$

min subject to	)			6	_	$3x_1$	_	$3x_2$
5	x	3	=	1	_	$3x_1$	—	$2x_2$
	$\overline{x}$	4	=	2	—	$2x_1$	+	$x_2$
	x	5	=	3	+	$x_1$	_	$3x_2$
				Ļ				
min subject to			$\frac{9}{2}$	+	$\frac{3}{2}$	$x_1 + $	$\frac{3}{2}x_3$	
subject to	$x_2$	=	$\frac{1}{2}$	_	$\frac{3}{2}a$	$x_1 - $	$\frac{1}{2}x_3$	
	$x_4$	=	$\frac{5}{2}$	_	$\frac{7}{2}$	$x_1 -$	$\frac{1}{2}x_3$	
	$x_5$	=	$\frac{3}{2}$	+	$\frac{11}{2}3$	$x_1 + $	$\frac{3}{2}x_3$	

$\min$				6		$3x_1$	_	$3x_2$
subject to								
	x	3	_	1	-	$3x_1$	_	$2x_2$
	x	4	=	2	_	$2x_1$	+	$x_2$
	x	5	=	3	+	$x_1$		$3x_2$
				↓ ↓				
min			$\frac{9}{2}$	+	$\frac{3}{2}a$	$x_1 +$	$\frac{3}{2}x_3$	
subject to	$x_2$	=	$\frac{1}{2}$	_	$\frac{3}{2}a$	$c_1 -$	$\frac{1}{2}x_3$	
	$x_4$	=	$\frac{5}{2}$	_	$\frac{7}{2}a$	$c_1 -$	$\frac{1}{2}x_3$	
	$x_5$	=	$\frac{3}{2}$	+	$\frac{11}{2}a$	$c_1 +$	$\frac{3}{2}x_3$	

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- Local move improves the objective value
- In a BFS, assume that

 $-b_1 > 0, b_2 > 0, ..., b_m > 0$ 

- there exists an entering variable e with  $c_e < 0$
- Then, the move pivot(e,l) is improving

while 
$$\exists 1 \leq i \leq n : c_i < 0$$
 do  
choose  $e$  such that  $c_e < 0$ ;  
 $l = \underset{i:a_{ie} < 0}{\operatorname{arg-min}} \frac{b_i}{-a_{ie}};$   
pivot $(e,l);$ 

- If
  - $-b_1, b_2, ..., b_m$  are strictly positive
  - objective function is bounded below
- Algorithm terminates with an optimal solution

• Selecting the leaving variable

$$l = \underset{i:a_{ie} < 0}{\operatorname{arg-min}} \frac{b_i}{-a_{ie}}$$

• No leaving variable!

min			6	_	$3x_1$		$3x_2$
subject to							
	$x_3$	=	1	+	$3x_1$	—	$2x_2$
	$x_4$	=	2	+	$2x_1$	+	$x_2$
	$x_5$	—	3	+	$x_1$		$3x_2$

Basic solution

$$\{x_1 = 0; x_2 = 0; x_3 = 1; x_4 = 2; x_5 = 3\}$$

- What if I increase the value of  $x_1$ 
  - Solution remains feasible, but
  - Value of objective function decreases

• Another issue: What if some  $b_i$  becomes zero?

min subject to			5	_	$3x_1$		$3x_2$
Subject to	$x_3$	—	0	_	$3x_1$	_	$2x_2$
	$x_4$	=	2	—	$2x_1$	+	$x_2$
	$x_5$	=	3	+	$x_1$	_	$3x_2$

• Leaving variable: *x*<sub>2</sub>



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#### Need to find a new way to guarantee termination

- Termination
  - Bland rule: select always the first entering variable lexicographically
  - Lexicographic pivoting rule: break ties when selecting the leaving variable
  - Pertubation methods

• How do I find my first BFS ?

min  $c_1 x_1 + \ldots + c_n x_n$ subject to  $a_{11} x_1 + \ldots + a_{1n} x_n = b_1$   $\ldots$  $a_{m1} x_1 + \ldots + a_{mn} x_n = b_m$ 

• Introduce artificial variables



• Easy BFS 😲



- Two-phase strategy
  - 1. First find a BFS (if one exists)
  - 2. Then, find optimal BFS

#### 1. Find a BFS

min							$y_1$	+	•••	+	$y_m$		
subject to	$a_{11}x_1$	+		+	$a_{1n}x_n$	+	$y_1$					=	$b_1$
	$a_{i1}x_1$	+	••••	+	$a_{in}x_n$			+	$y_i$			=	$b_i$
	$a_{m1}x_1$	+		+	$a_{mn}x_n$					+	$y_m$	=	$b_m$

- Feasible if the objective value is 0
  - i.e., all  $y_i$ 's are 0, and there is a BFS without  $y_i$  (almost always)