# MA427 Lecture 3 Basic solutions and the Simplex Method

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# Today's lecture

- Standard equality form: basic solutions and their existence
- Carathéodory's theorem

#### Simplex Method

- the tableau form
- connection to duality
- pivot steps
- cycling: Bland's rule

$$A \in \mathbb{R}^{m \times n}$$
,  $b \in \mathbb{R}^m$ .

$$Ax = b$$
  
 $x \ge 0$ 

Assumption: 
$$rk(A) = m$$
.

#### **Definition**

A set  $B \subseteq \{1, ..., n\}$  is said a *basis* of A if

- ▶ |B| = m;
- ▶ the vectors  $A_j$ ,  $j \in B$ , are linearly independent.

### Example

$$\begin{bmatrix} 1 & 2 & 0 & 1 & 0 & -6 \\ 0 & 1 & 1 & 3 & -2 & -1 \\ 1 & 2 & 1 & 3 & -1 & -5 \end{bmatrix} x = \begin{bmatrix} 11 \\ 6 \\ 13 \end{bmatrix}.$$
$$x \ge 0$$

 $B = \{1, 2, 6\}$  is a basis.

$$A_B = \left[ \begin{array}{rrr} 1 & 2 & -6 \\ 0 & 1 & -1 \\ 1 & 2 & -5 \end{array} \right].$$

 $B = \{2, 5, 6\}$  is not a basis.

$$A_B = \left[ \begin{array}{rrr} 2 & 0 & -6 \\ 1 & -2 & -1 \\ 2 & -1 & -5 \end{array} \right].$$

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#### Proposition

A point  $x^* \in \mathbb{R}^n$  is a basic feasible solution of  $Ax = b, x \ge 0$  if and only if it is feasible and  $\exists$  a basis B such that  $x_j^* = 0$  for every  $j \notin B$ .

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#### Proof.

- $x^*$  is basic feasible to Ax = b,  $x \ge 0$  if and only if there n linearly independent inequalities.
- ▶ Ax = b already gives m linearly independent ones, therefore we need n m binding constraints  $x_j \ge 0$ ,  $j \in N$ , |N| = n m.

$$R = \left(\begin{array}{c|c} A_B & A_N \\ \hline \mathbf{0} & I \end{array}\right),$$

▶  $det(R) = det(A_B)$ . Consequently,  $x^*$  is a basis if and only if  $det(A_B) \neq 0$ , that is, the columns of  $A_B$  are lin. independent.

$$\begin{bmatrix} 1 & 2 & 0 & 1 & 0 & -6 \\ 0 & 1 & 1 & 3 & -2 & -1 \\ 1 & 2 & 1 & 3 & -1 & -5 \end{bmatrix} x = \begin{bmatrix} 11 \\ 6 \\ 13 \end{bmatrix}.$$
$$x \ge 0$$

 $\bar{x} = (7, 8, 0, 0, 0, 2)$  basic (feasible) solution.

- lt is feasible.
- $\triangleright$  *B* = {1, 2, 6} is a basis
- $\bar{x}_3, \bar{x}_4, \bar{x}_5 = 0$

To see that the previous point is basic: the inequalities binding at  $\bar{x}$ .

$$\begin{bmatrix} 1 & 2 & 0 & 1 & 0 & | & -6 \\ 0 & 1 & 1 & 3 & -2 & | & -1 \\ 1 & 2 & 1 & 3 & -1 & | & -5 \\ \hline 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \end{bmatrix} x = \begin{bmatrix} 11 \\ 6 \\ 13 \\ 0 \\ 0 \end{bmatrix}.$$

The above matrix has the same determinant as

$$A_B = \left[ \begin{array}{rrr} 1 & 2 & -6 \\ 0 & 1 & -1 \\ 1 & 2 & -5 \end{array} \right].$$

We will need this more general notion.

#### Definition

A point  $x^* \in \mathbb{R}^n$  is a basic solution of Ax = b,  $x \ge 0$ , if  $Ax^* = b$  and there exists a basis B of A such that  $x_i^* = 0$  for every  $j \notin B$ .

That is, we consider also basic solutions that are **not** feasible. This will be needed when discussing the dual simplex method.

$$Ax = b$$
$$x \ge 0$$

#### Lemma

Given a basis B, the point

$$\bar{x}_B = A_B^{-1}b;$$
  
 $\bar{x}_N = 0$ 

is the only one such that  $A\bar{x} = b$  and  $\bar{x}_j = 0 \ \forall j \notin B$ .

The above is the basic solution relative to B. If  $\bar{x}$  is feasible, then B is feasible basis.

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$$x \ge 0$$

 $B = \{1, 2, 6\}$  is a basis.

$$A_B^{-1} = \left[ \begin{array}{rrr} -3 & -2 & 4 \\ -1 & 1 & 1 \\ -1 & 0 & 1 \end{array} \right].$$

 $\bar{x} = (7, 8, 0, 0, 0, 2)$  basic (feasible) solution relative to B.

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 $\bar{x} = (-1, 0, 4, 0, 0, -2)$  basic (infeasible) solution relative to B.

#### Theorem

If the LP problem

$$\max c^{\top} x$$

$$Ax = b$$

$$x \ge 0$$

has a finite optimum, there exists an optimal solution  $x^*$  which is a basic feasible solution.

#### Two proofs:

- Simple direct proof now.
- Consequence of the Simplex Method.

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#### Proof.

- Select an optimal solution x\* with the highest number of zero components.
- For a contradiction, assume that  $x^*$  is not basic. Let  $S = \{j : x_j^* > 0\}.$

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#### Proof.

- ► Select an optimal solution *x*\* with the *highest number of zero components*.
- For a contradiction, assume that  $x^*$  is not basic. Let  $S = \{j : x_i^* > 0\}.$
- ► Thus,  $\{A_j : j \in S\}$  is not linearly independent. Thus,  $\exists z_j, j \in S : \sum_j A_j z_j = 0$ . Let

$$d_j = \begin{cases} z_j & \text{if } j \in S \\ 0 & \text{if } j \notin S \end{cases}$$

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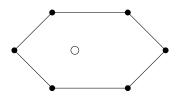
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- For a small  $\varepsilon > 0$ ,  $x^* \varepsilon d$ ,  $x^* + \varepsilon d$  are both feasible. Thus,  $c^\top d = 0$  and therefore the are both optimal.

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- Assume  $\exists i: d_i > 0$ . Select  $\bar{t} \geq 0$  as the largest value such that  $x^* \bar{t}d$  is feasible.
- $x' = x^* \bar{t}d$  is also optimal and has more zero components than  $x^*$ , a contradiction.

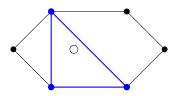
#### Theorem (Carathéodory)

If a point  $z \in \mathbb{R}^n$  is a convex combination of points in some set  $X \subseteq \mathbb{R}^n$ , then it is a convex combination of at most  $\dim(X) + 1$  affinely independent points in X.



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#### Proof.

- lacksquare  $X = \{v^1, \dots, v^k\}$ . Define  $A \in \mathbb{R}^{n+1 \times k}$ :  $A_i = \binom{v'}{1}$ .
- ▶ z is a convex combination if the following system is feasible.

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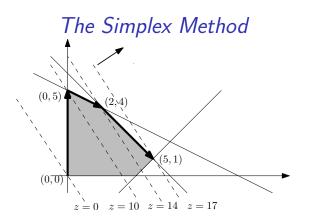
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$$A\lambda = z$$
  
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- ▶ Select a basic feasible solution. The columns  $\{A_i : \lambda_i > 0\}$  are linearly independent, and there are at most n+1 of them.
- ▶ This shows that  $\{v^i : \lambda_i > 0\}$  are affinely independent.



In standard equality form

Feasible basis:  $\{3,4,5\}$  Basic solution:  $(0,0,6,10,4)^{\top}$ 

Basic solution:  $(0,0,6,10,4)^{\top}$ . Basis:  $\{3,4,5\}$ .

If we increase  $x_2$  by  $t \ge 0$  and leave  $x_1 = 0$ , the objective value increases by 2t.

The remaining components must become

$$x_3(t) = 6 - t$$
  
 $x_4(t) = 10 - 2t$   
 $x_5(t) = 4 + t$ 

The maximum t we can choose is t = 5.

- Current solution (0, 5, 1, 0, 9). Basis:  $\{2, 3, 5\}$ .
- ▶ We express everything in terms of the nonbasic variables.

Basic solution:  $(0,5,1,0,9)^{\top}$ . Feasible basis:  $\{2,3,5\}$ . If we increase  $x_1$  by  $t \ge 0$  and leave  $x_4 = 0$ , the objective value increases by 2t.

The remaining components must become

$$x_2(t) = 5 - \frac{1}{2}t$$
  
 $x_3(t) = 1 - \frac{1}{2}t$   
 $x_5(t) = 9 - \frac{3}{2}t$ 

Basic solution:  $(2,4,0,0,6)^{\top}$ . Feasible basis:  $\{1,2,5\}$ .

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...

#### Continue until

- either we cannot increase the objective value any further
- we find an unbounded direction.

### The Simplex Method

We assume that the initial LP is in standard equality form.

$$\begin{array}{ccc}
\text{max} & c^{\top} x \\
Ax = & b \\
x \ge & 0
\end{array}$$

Assumption: 
$$rk(A) = m$$
.

- ► At every iteration we maintain a basis *B*, defining a basic feasible solution.
- ▶ The LP is transformed, via row reductions, to one where
  - ➤ The objective function is expressed in terms of the nonbasic variables only,
  - each basic variable is written in terms of the nonbasic ones.
- Increasing the value of a nonbasic variable with positive coefficient in the objective function gives a solution with higher value.

#### Tableau form

where

$$\bar{A}_{N} = A_{B}^{-1}A_{N};$$

$$\bar{b} = A_{B}^{-1}b;$$

$$\bar{c} = c - A^{\top}A_{B}^{-1}^{\top}c_{B}; \quad (reduced costs)$$

$$\bar{z} = c_{B}^{\top}A_{B}^{-1}b.$$

Tableau with respect to B

1	0	$-ar{c}_{N}^{ op}$	Ī	
0	I	$ar{\mathcal{A}}_{\mathcal{N}}$	$\bar{b}$	

# Example of problem in tableau form

Basis: 
$$B = \{1, 2, 5\}$$
 $x_1 = \{1, 2, 5\}$ 
 $x_1 + 4x_3 - x_4 = 14$ 
 $x_1 + 2x_3 - x_4 = 2$ 
 $x_1 + x_2 - x_3 + x_4 = 4$ 
 $x_1 - 3x_3 + 2x_4 + x_5 = 6$ 
 $x_1, x_2, x_3, x_4, x_5 \ge 0$ 

			4			
0	1	0	2	-1	0	2
0	0	1	-1	1	0	4
0	0	0	2 -1 -3	2	1	6

If  $B = \{B[1], \dots, B[m]\}$ , we can write the problem in tableau form

- $ightharpoonup ar{c}_i$ ,  $j=1,\ldots,n$  are said the reduced costs.
- $ightharpoonup x_{B[h]}$  is said the basic variable in row h.

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Let  $\bar{x}$  be the basic feasible solution relative to B.

▶ Case 1.  $\bar{c}_j \leq 0$  for all  $j \in N$ :  $\bar{x}$  is optimal

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We can read off a dual optimal solution certifying the optimality of  $\bar{x}$ .

# Dual optimal solution

$$\bar{A}_{N} = A_{B}^{-1}A_{N};$$

$$\bar{b} = A_{B}^{-1}b;$$

$$\bar{c} = c - A^{\top}A_{B}^{-1}{}^{\top}c_{B} \leq 0; \quad (reduced\ costs)$$

$$\bar{z} = c_{B}^{\top}A_{B}^{-1}b.$$

$$\bar{x}_{j} = \begin{cases} \bar{b}_{j} & \text{if } j \in B \\ 0 & \text{if } j \in N \end{cases} \qquad \bar{y} = A_{B}^{-1}{}^{\top}c_{B}$$

# Dual optimal solution

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 $\bar{x}$  is a feasible primal,  $\bar{y}$  a feasible dual solution, and they satisfy complementary slackness.

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- ▶ Case 1.  $\bar{c}_j \leq 0$  for all  $j \in N$ :  $\bar{x}$  is optimal
- ▶ Case 2. There exists  $k \in N$  such that  $\bar{c}_k > 0$ : if we increase  $x_k$  by  $t \ge 0$  leaving  $x_j = 0$  for all  $j \in N \setminus \{k\}$ , then the objective value increases by  $\bar{c}_k t$ .

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What is the maximum we can increase t?

#### Minimum ratio rule

The largest  $\bar{t}$  such that the new solution  $x(\bar{t})$  is feasible is

$$\bar{t} = \min_{i \in \{1, \dots, m\} : \bar{a}_{ik} > 0} \left\{ \frac{\bar{b}_i}{\bar{a}_{ik}} \right\}.$$

#### One iteration

*Basis:* {1, 2, 5}.

Entering variable: x<sub>4</sub>.

Exiting variable:  $x_5$  (since min $\{\cdot, \frac{4}{1}, \frac{6}{2}\} = 3$ ).

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Entering variable: x4.

Exiting variable:  $x_5$  (since min $\{\cdot, \frac{4}{1}, \frac{6}{2}\} = 3$ ).

#### Pivot.

$$z$$
 + 1.5 $x_3$  - 0.25 $x_4$  = 3  
+ 0.5 $x_3$  - 0.25 $x_4$  = 2  
 $x_2$  - 0.5 $x_3$  - 0.25 $x_4$  = 1

Feasible basis:  $\{1,2\}$ . Basic solution:  $(2,1,0,0)^{T}$ .

$$z$$
 + 1.5 $x_3$  - 0.25 $x_4$  = 3  
 $x_1$  + 0.5 $x_3$  - 0.25 $x_4$  = 2  
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Feasible basis:  $\{1,2\}$ . Basic solution:  $(2,1,0,0)^{\top}$ . If we increase  $x_4$  by  $t \ge 0$  leaving  $x_3 = 0$ , the objective value increases by 0.25t.

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$$x_1(t) = 2 + 0.25t$$
  
 $x_2(t) = 1 + 0.25t$   
 $x_3(t) = 0$   
 $x_4(t) = t$ 

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$$x_1(t) = 2 + 0.25t$$
  
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x(t) is a family of feasible solutions,

$$\lim_{t\to+\infty}c^{\top}x(t)=+\infty.$$

**Input:** 
$$A \in \mathbb{R}^{m \times n}$$
,  $b \in \mathbb{R}^m$ ,  $c \in \mathbb{R}^n$ , a feasible basis  $B = \{B[1], \dots, B[m]\}$  for  $Ax = b, x \ge 0$ ;

**Output:** An optimal solution for  $\max\{c^{\top}x: Ax=b, x\geq 0\}$ , or we determine that the problem is unbounded.

- 1. Compute the tableau relative to the current basis *B*;
- 2. If  $\bar{c}_j \leq 0$  for all  $j \in N$ , then the basic feasible solution relative to B is *optimal*, STOP.
- 3. Otherwise, choose k such that  $\bar{c}_k > 0$ ;
  - 3a. If  $\bar{a}_{ik} \leq 0 \ \forall i \in \{1, \dots, m\}$ , then the problem is *unbounded*, *STOP*.
  - 3b. Otherwise, choose  $h \in \{1, ..., m\}$  such that

$$\bar{a}_{hk} > 0$$
 and  $\bar{b}_h/\bar{a}_{hk} = \min_{i:\bar{a}_{ik}>0} \bar{b}_i/\bar{a}_{ik}$ ;

Set B[h] := k, return to 1. ( $x_k$  enters the basis in row h,  $x_{B[h]}$  leaves the basis)

# Pivots: $x_k$ enters, $x_h$ leaves

Z	$x_1$	• • •	$x_h$	• • •	$x_m$	$x_{m+1}$	• • •	$x_k$	$\cdots x_n$	
1	0		0		0			$-\bar{c}_k$		Ī
0	1		0					$\bar{a}_{1k}$		$ar{b}_1$
:		٠.	÷					:		:
0			1					ā <sub>hk</sub>		$ar{b}_h$
:			:	٠				:		:
0			0		1			ā <sub>mk</sub>		$ar{b}_m$

1	0		$\frac{\bar{c}_k}{\bar{a}_{hk}}$		0	 0	 $ar{z} + rac{ar{c}_k ar{b}_h}{ar{a}_{hk}}$
0	1		$-\frac{\bar{a}_{1k}}{\bar{a}_{hk}}$			0	$ar{b}_1 - rac{ar{a}_{1k}ar{b}_h}{ar{a}_{hk}}$
:		٠	:			:	:
0			$\frac{1}{\bar{a}_{hk}}$			1	$\frac{\bar{b}_h}{\bar{a}_{hk}}$
:			:	·		:	i
0			$-\frac{\bar{a}_{mk}}{\bar{a}_{hk}}$		1	0	$ar{b}_m - rac{ar{a}_{mk}ar{b}_h}{ar{a}_{hk}}$

# Termination of the Simplex

New solution

$$x_k(\bar{t}) = \bar{t};$$

$$x_{B[i]}(\bar{t}) = \bar{b}_i - \bar{t}\bar{a}_{ik}, \quad i = 1, \dots, m;$$

$$x_j(\bar{t}) = 0, \quad j \in N \setminus \{k\}.$$

where

$$ar{t} = \min \left\{ rac{ar{b}_i}{ar{a}_{ik}} \, : \, i = 1, \ldots, m, \,\, ar{a}_{ik} > 0 
ight\}.$$

Entering variable: some  $x_k$  such that  $\bar{c}_k > 0$ .

Exiting variable: some  $x_{B[h]}$  such that  $ar{a}_{hk}>0$  and  $ar{t}=rac{b_h}{ar{a}_{hk}}$ 

#### **Termination**

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$$ar{t} := \min_{i \in \{1, \dots, m\} : \, ar{a}_{ik} > 0} \left\{ rac{ar{b}_i}{ar{a}_{ik}} 
ight\}$$

- ▶ If  $\bar{t} > 0$ , the objective value increases strictly.
- If  $\bar{t} = 0$ , the basis changes, but the corresponding basic feasible solution remains the same.

# Cycling example

Bad *tie-breaking rule:* choose the entering variable with highest reduced cost, and the exiting variable with highest column coefficient.

1	-2.3	-2.15	13.55	0.4	0	0	0
0	0.4	$0.2 \\ -1.4$	-1.4	-0.2	1	0	0
0	-7.8	-1.4	7.8	0.4	0	1	0

1	0	-1	5.5	-0.75	5.75		0
0	1	0.5	-3.5	-0.5	2.5	0	0
0	0	2.5	-19.5	-3.5	19.5	0 1	0

1	0	0	-2.3	-2.15	13.55	0.4	0
0	1 0	0	0.4	0.2	-1.4	-0.2	0
0	0	1	-7.8	-1.4	7.8	0.4	0

This is the same tableau as in the beginning, only shift by two position. Repeating other two times (i.e, after 4 other pivots), we return the original tableau.

## Degeneracy

#### Definition

A basis B is said to be degenerate if  $\bar{b}_i = 0$  for some  $i \in \{1, ..., m\}$  (where  $\bar{b} = A_B^{-1}b$ ).

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- ▶ If all bases are non-degenerate, then the simplex method terminates regardlessly of how we choose the variables that enters or leaves.
- ▶ If there are degenerate bases, we could cycle.

To prevent cycling, we need to be careful in how we choose the entering and exiting variables.

# An anti-cycling rule

#### Bland's rule:

- Among all variables with positive reduced cost, choose as entering variable the variable  $x_k$  such that the index k is the smallest possible.
- Let  $\bar{t} = \min\{\frac{\bar{b}_i}{\bar{a}_{ik}} : \bar{a}_{ik} > 0\}$ . Choose as exiting variable the variable  $x_{B[h]}$  such that  $\bar{a}_{hk} > 0$ ,  $\frac{\bar{b}_h}{\bar{a}_{hk}} = \bar{t}$ , and such that B[h] is smallest possible.

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*QUIZ*: Which are the entering and exiting variables according to Bland's rule?

(A) Enter:  $x_2$ , exit:  $x_4$ . (B) Enter:  $x_2$ , exit:  $x_5$ .

(C) Enter:  $x_3$ , exit:  $x_1$ .

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- Let  $\overline{t} = \min\{\frac{\overline{b}_i}{\overline{a}_{ik}}: \overline{a}_{ik} > 0\}$ . Choose as exiting variable the variable  $x_{B[h]}$  such that  $\overline{a}_{hk} > 0$ ,  $\frac{\overline{b}_h}{\overline{a}_{hk}} = \overline{t}$ , and such that B[h] is smallest possible.

#### **Theorem**

The simplex method with Bland's pivot rule terminates for every possible instance of an LP problem and every possible choice of starting feasible basis.