

# International Doctoral School Algorithmic Decision Theory: MCDA and MOO

## Lecture 2: Multiobjective Linear Programming

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# Overview

- 1 Multiobjective Linear Programming
  - Formulation and Example
  - Solving MOLPs by Weighted Sums
- 2 Biobjective LPs and Parametric Simplex
  - The Parametric Simplex Algorithm
  - Biobjective Linear Programmes: Example
- 3 Multiobjective Simplex Method
  - A Multiobjective Simplex Algorithm
  - Multiobjective Simplex: Examples

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- Variables  $x \in \mathbb{R}^n$
- Objective function  $Cx$  where  $C \in \mathbb{R}^{p \times n}$
- Constraints  $Ax = b$  where  $A \in \mathbb{R}^{m \times n}$  and  $b \in \mathbb{R}^m$

$$\min \{Cx : Ax = b, x \geq 0\} \quad (1)$$

$$X = \{x \in \mathbb{R}^n : Ax = b, x \geq 0\}$$

is the **feasible set in decision space**

$$Y = \{Cx : x \in X\}$$

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## Example

$$\begin{aligned} \min \quad & \begin{pmatrix} 3x_1 + x_2 \\ -x_1 - 2x_2 \end{pmatrix} \\ \text{subject to} \quad & x_2 \leq 3 \\ & 3x_1 - x_2 \leq 6 \\ & x \geq 0 \end{aligned}$$

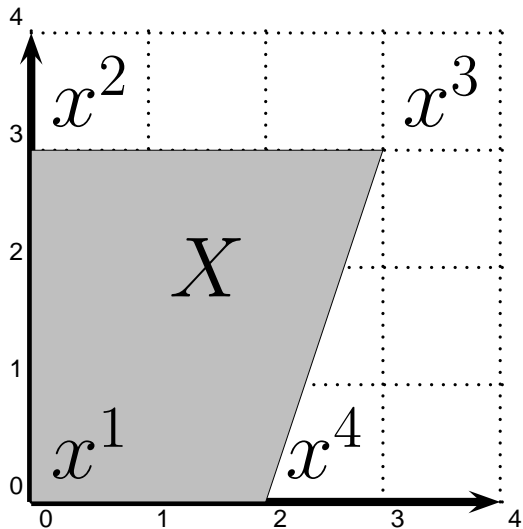
$$C = \begin{pmatrix} 3 & 1 \\ -1 & -2 \end{pmatrix} \quad A = \begin{pmatrix} 0 & 1 & 1 & 0 \\ 3 & -1 & 0 & 1 \end{pmatrix} \quad b = \begin{pmatrix} 3 \\ 6 \end{pmatrix}$$



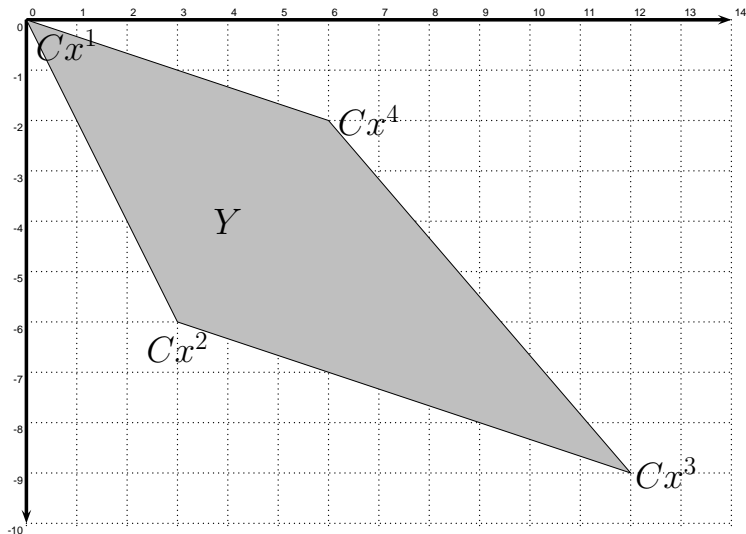
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Feasible set in decision space



Feasible set in objective space

## Definition

Let  $\hat{x} \in X$  be a feasible solution of the MOLP (1) and let  $\hat{y} = C\hat{x}$ .

- $\hat{x}$  is called **weakly efficient** if there is no  $x \in X$  such that  $Cx < C\hat{x}$ ;  $\hat{y} = C\hat{x}$  is called **weakly nondominated**.
- $\hat{x}$  is called **efficient** if there is no  $x \in X$  such that  $Cx \leq C\hat{x}$ ;  $\hat{y} = C\hat{x}$  is called **nondominated**.
- $\hat{x}$  is called **properly efficient** if it is efficient and if there exists a real number  $M > 0$  such that for all  $i$  and  $x$  with  $c_i^T x < c_i^T \hat{x}$  there is an index  $j$  and  $M > 0$  such that  $c_j^T x > c_j^T \hat{x}$  and

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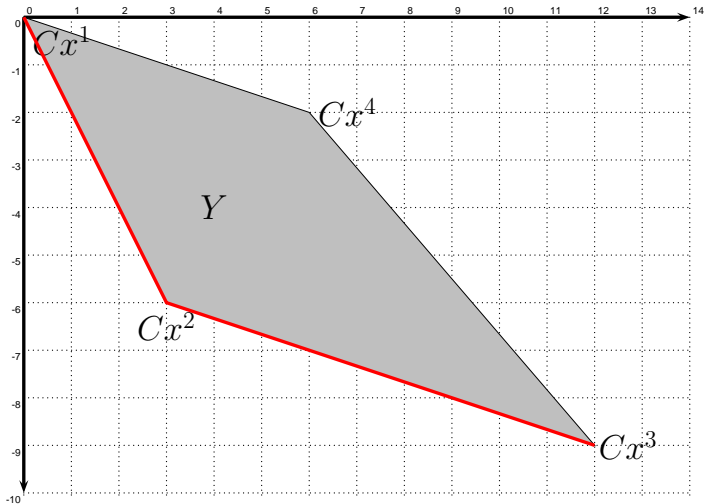
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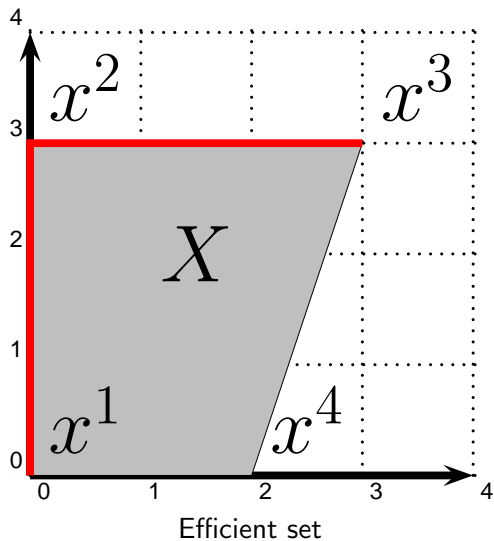
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Nondominated set





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- Let  $\lambda_1, \dots, \lambda_p \geq 0$  and consider

$$LP(\lambda) \quad \min \sum_{k=1}^p \lambda_k c_k^T x = \min \lambda^T Cx$$

subject to  $Ax = b$   
 $x \geq 0$

with some vector  $\lambda \geq 0$  (Why not  $\lambda = 0$  or  $\lambda \leq 0$ ?)

- $LP(\lambda)$  is a linear programme that can be solved by the Simplex method
- If  $\lambda > 0$  then optimal solution of  $LP(\lambda)$  is properly efficient
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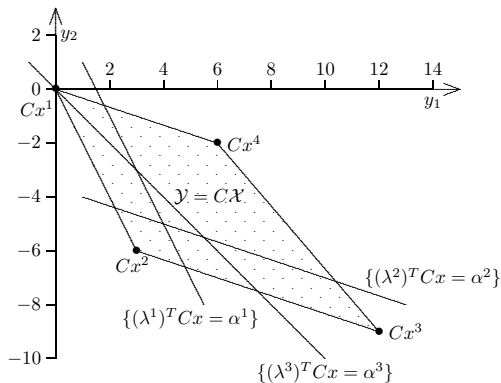
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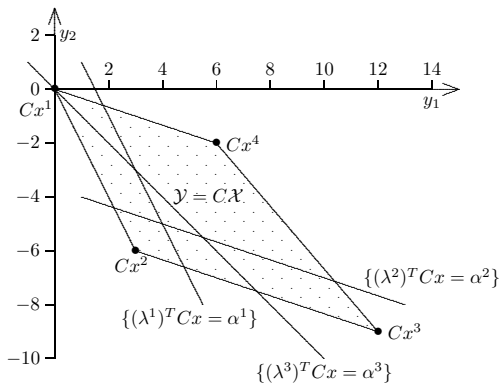
## Illustration in objective space



$$\lambda^1 = (2, 1), \lambda^2 = (1, 3), \lambda^3 = (1, 1)$$



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- $y \in \mathbb{R}^p$  satisfying  $\lambda^T y = \alpha$  define a straight line (hyperplane)
- Since  $y = Cx$  and  $\lambda^T Cx$  is minimised, we push the line towards the origin (left and down)
- When the line only touches  $Y$  nondominated points are found
- Nondominated points  $Y_N$  are on the boundary of  $Y$
- $Y$  is convex polyhedron and has finite number of facets.  $Y_N$  consists of finitely many facets of  $Y$ . The normal of the facet can serve as weight vector  $\lambda$

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If  $\hat{x} \in X$  is efficient, does there exist  $\lambda > 0$  such that  $\hat{x}$  is optimal solution to

$$\min\{\lambda^T Cx : Ax = b, x \geq 0\}?$$

### Lemma

A feasible solution  $x^0 \in X$  is efficient if and only if the linear programme

$$\begin{array}{ll} \max & e^T z \\ \text{subject to} & Ax = b \\ & Cx + Iz = Cx^0 \\ & x, z \geq 0, \end{array} \quad (2)$$

where  $e^T = (1, \dots, 1) \in \mathbb{R}^p$  and  $I$  is the  $p \times p$  identity matrix, has an optimal solution  $(\hat{x}, \hat{z})$  with  $\hat{z} = 0$ .

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$$\begin{aligned} \min \quad & u^T b + w^T C x^0 \\ \text{subject to} \quad & u^T A + w^T C \geq 0 \\ & w \geq e \\ & u \in \mathbb{R}^m \end{aligned} \tag{3}$$

has an optimal solution  $(\hat{u}, \hat{w})$  with  $\hat{u}^T b + \hat{w}^T C x^0 = 0$ .

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The LP (3) is the dual of the LP (2) □

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## Proof.

- Let  $x^0 \in X_E$
- By Lemma 4 LP (3) has an optimal solution  $(\hat{u}, \hat{w})$  such that

$$\hat{u}^T b = -\hat{w}^T C x^0 \quad (5)$$

- $\hat{u}$  is also an optimal solution of the LP

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- Modification of the **Simplex algorithm** for LPs with two objectives

$$\begin{array}{ll} \min & ((c^1)^T x, (c^2)^T x) \\ \text{subject to} & Ax = b \\ & x \geq 0 \end{array} \quad (8)$$

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### Algorithm (Parametric Simplex for biobjective LPs)

*Input:* Data  $A, b, C$  for a biobjective LP.

*Phase I:* Solve the auxiliary LP for Phase I using the Simplex algorithm. If the optimal value is positive, STOP,  $X = \emptyset$ . Otherwise let  $\mathcal{B}$  be an optimal basis.

*Phase II:* Solve the LP (9) for  $\lambda = 1$  starting from basis  $\mathcal{B}$  found in Phase I yielding an optimal basis  $\tilde{\mathcal{B}}$ . Compute  $\tilde{A}$  and  $\tilde{b}$ .

*Phase III:* While  $\mathcal{I} = \{i \in \mathcal{N} : \bar{c}_i^2 < 0, \bar{c}_i^1 \geq 0\} \neq \emptyset$ .

$$\lambda := \max_{i \in \mathcal{I}} \frac{-\bar{c}_i^2}{\bar{c}_i^1 - \bar{c}_i^2}.$$

$$s \in \operatorname{argmax} \left\{ i \in \mathcal{I} : \frac{-\bar{c}_i^2}{\bar{c}_i^1 - \bar{c}_i^2} \right\}.$$

$$r \in \operatorname{argmin} \left\{ j \in \mathcal{B} : \frac{\tilde{b}_j}{\tilde{A}_{js}}, \tilde{A}_{js} > 0 \right\}.$$

Let  $\mathcal{B} := (\mathcal{B} \setminus \{r\}) \cup \{s\}$  and update  $\tilde{A}$  and  $\tilde{b}$ .

End while.

*Output:* Sequence of  $\lambda$ -values and sequence of optimal BFSs.

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## Example

$$\begin{array}{ll} \min & \begin{pmatrix} 3x_1 + x_2 \\ -x_1 - 2x_2 \end{pmatrix} \\ \text{subject to} & \begin{array}{r} x_2 \leq 3 \\ 3x_1 - x_2 \leq 6 \\ x \geq 0 \end{array} \end{array}$$

$LP(\lambda)$

$$\begin{array}{ll} \min & (4\lambda - 1)x_1 + (3\lambda - 2)x_2 \\ \text{subject to} & \begin{array}{r} x_2 + x_3 = 3 \\ 3x_1 - x_2 + x_4 = 6 \\ x \geq 0. \end{array} \end{array}$$

- Use Simplex tableaus showing reduced cost vectors  $\bar{c}^1$  and  $\bar{c}^2$
- Optimal basis for  $\lambda = 1$  is  $\mathcal{B} = \{3, 4\}$ , optimal basic feasible solution  $x = (0, 0, 3, 6)$
- Start with Phase 3



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Iteration 1:

$\bar{c}^1$	3	1	0	0	0
$\bar{c}^2$	-1	-2	0	0	0
$x_3$	0	1	1	0	3
$x_4$	3	-1	0	1	6

$$\lambda = 1, \bar{c}(\lambda) = (3, 1, 0, 0), \mathcal{B}^1 = \{3, 4\}, x^1 = (0, 0, 3, 6)$$

$$\mathcal{I} = \{1, 2\}, \lambda' = \max \left\{ \frac{1}{3+1}, \frac{2}{1+2} \right\} = \frac{2}{3}$$

$$s = 2, r = 3$$

## Iteration 2

$\bar{c}^1$	3	0	-1	0	-3
$\bar{c}^2$	-1	0	2	0	6
$x_2$	0	1	1	0	3
$x_4$	3	0	1	1	9

$$\lambda = 2/3, \bar{c}(\lambda) = (5/3, 0, 0, 0), \mathcal{B}^2 = \{2, 4\}, x^2 = (0, 3, 0, 9)$$

$$\mathcal{I} = \{1\}, \lambda' = \max \left\{ \frac{1}{3+1} \right\} = \frac{1}{4}$$

$$s = 1, r = 4$$

## Iteration 3

$\bar{c}^1$	0	0	-2	-1	-12
$\bar{c}^2$	0	0	7/3	1/3	9
$x_2$	0	1	1	0	3
$x_1$	1	0	1/3	1/3	3

$$\lambda = 1/4, \bar{c}(\lambda) = (0, 0, 5/4, 0), \mathcal{B}^3 = \{1, 2\}, x^3 = (3, 3, 0, 0)$$
$$\mathcal{I} = \emptyset$$

- Weight values  $\lambda^1 = 1, \lambda^2 = 2/3, \lambda^3 = 1/4, \lambda^4 = 0$
- Basic feasible solutions  $x^1, x^2, x^3$
- In each iteration  $\bar{c}(\lambda)$  can be calculated with the previous and current  $\bar{c}^1$  and  $\bar{c}^2$ .
- Basis  $\mathcal{B}^1 = (3, 4)$  and BFS  $x^1 = (0, 0, 3, 6)$  are optimal for  $\lambda \in [2/3, 1]$ .
- Basis  $\mathcal{B}^2 = (2, 4)$  and BFS  $x^2 = (0, 3, 0, 9)$  are optimal for  $\lambda \in [1/4, 2/3]$ , and
- Basis  $\mathcal{B}^3 = (1, 2)$  and BFS  $x^3 = (3, 3, 0, 0)$  are optimal for  $\lambda \in [0, 1/4]$ .
- Objective vectors for basic feasible solutions:  $Cx^1 = (0, 0)$ ,  $Cx^2 = (3, -6)$ , and  $Cx^3 = (12, -9)$

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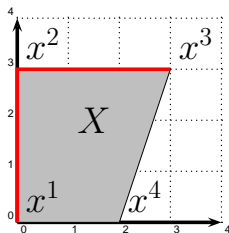
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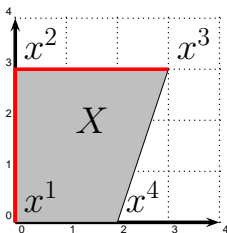


Feasible set in decision space and  
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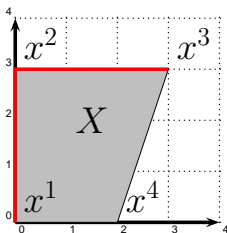
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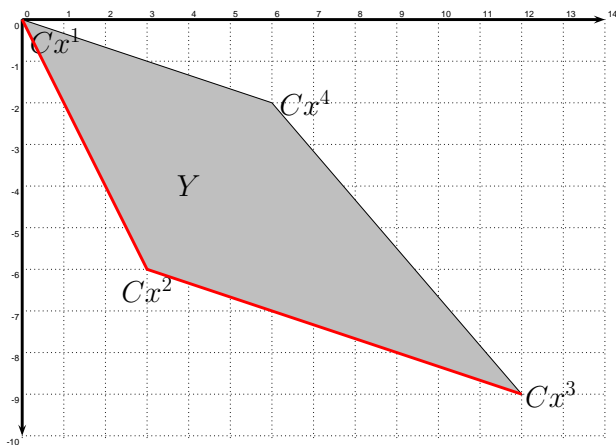
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Objective space and nondominated set



- Algorithm finds **all nondominated extreme points** in objective space and **one efficient bfs** for each of those
- Algorithm **does not find all efficient solutions** just as Simplex algorithm does not find all optimal solutions of an LP

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$$\begin{array}{ll} \min & (x_1, x_2)^T \\ \text{subject to} & 0 \leq x_i \leq 1 \quad i = 1, 2, 3 \end{array}$$

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# Overview

- 1 Multiobjective Linear Programming
  - Formulation and Example
  - Solving MOLPs by Weighted Sums
- 2 Biobjective LPs and Parametric Simplex
  - The Parametric Simplex Algorithm
  - Biobjective Linear Programmes: Example
- 3 Multiobjective Simplex Method
  - A Multiobjective Simplex Algorithm
  - Multiobjective Simplex: Examples

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- Let  $B$  be a basis and  $\bar{C} = C - C_B A_B^{-1} A$  and  $R = \bar{C}_N$
- How to calculate “critical”  $\lambda$  if  $p > 2$ ?
- At  $B_1$ :  $\bar{C}_N = \begin{pmatrix} 3 & 1 \\ -1 & -2 \end{pmatrix}$ ,  $\lambda' = 2/3$ ,  $\lambda = (2/3, 1/3)^T$  and  $\lambda^T \bar{C}_N = (5/3, 0)^T$
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## Proof.

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It is not possible to define efficient nonbasic variables by the existence of a column in  $R$  with positive and negative entries

### Example

$$R = \begin{pmatrix} 3 & -2 \\ -2 & 1 \end{pmatrix}$$

- $\lambda^T r^2 = 0$  requires  $\lambda_2 = 2\lambda_1$
- $\lambda^T r^1 \geq 0$  requires  $-\lambda_1 \geq 0$ , an impossibility for  $\lambda > 0$

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- $x_j$  efficient entering variable at basis  $\mathcal{B}$
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## How to identify efficient nonbasic variables?

### Theorem

Let  $\mathcal{B}$  be an efficient basis and let  $x_j$  be a nonbasic variable.  
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Proof.

- The dual of (14) is

$$\begin{array}{ll} \max & e^T v \\ \text{subject to} & Rz - r^j \delta + lv = 0 \\ & z, \delta, v \geq 0. \end{array} \quad (15)$$

□

Need to show: ALL efficient bases can be reached by efficient pivots

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Two efficient bases  $\mathcal{B}$  and  $\hat{\mathcal{B}}$  are called **connected** if one can be obtained from the other by performing only efficient pivots.

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- $\mathcal{X} \neq \emptyset$  but  $\mathcal{X}_E = \emptyset$ , no efficient solutions
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result in three phase multiobjective Simplex algorithm

- Phase I: Solve  $\min\{e^T z : Ax + Iz = b, x \geq 0, z \geq 0\}$   
 If optimal value is nonzero,  $\mathcal{X} = \emptyset$   
 Otherwise find bfs of  $Ax = b, x \geq 0$  from optimal solution
- Phase II: Find efficient bfs by solving appropriate  $LP(\lambda)$   
 Note:  $LP(\lambda)$  can be unbounded even if  $\mathcal{X}_E \neq \emptyset$   
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## Algorithm (Multicriteria Simplex Algorithm.)

*Input: Data  $A, b, C$  of an MOLP.*

*Initialization: Set  $\mathcal{L}_1 := \emptyset, \mathcal{L}_2 := \emptyset$ .*

*Phase I: Solve the LP  $\min\{e^T z : Ax + Iz = b, x, z \geq 0\}$ .*

*If the optimal value of this LP is nonzero, STOP,  $\mathcal{X} = \emptyset$ .*

*Otherwise let  $x^0$  be a basic feasible solution of the MOLP.*

*Phase II: Solve the LP*

*$\min\{u^T b + w^T Cx^0 : u^T A + w^T C \geq 0, w \geq e\}$ .*

*If the problem is infeasible, STOP,  $\mathcal{X}_E = \emptyset$ .*

*Otherwise let  $(\hat{u}, \hat{w})$  be an optimal solution.*

*Find an optimal basis  $\mathcal{B}$  of the LP  $\min\{\hat{w}^T Cx : Ax = b, x \geq 0\}$ .*

*$\mathcal{L}_1 := \{\mathcal{B}\}, \mathcal{L}_2 := \emptyset$ .*

## Algorithm

Phase III:

While  $\mathcal{L}_1 \neq \emptyset$

Choose  $\mathcal{B}$  in  $\mathcal{L}_1$ , set  $\mathcal{L}_1 := \mathcal{L}_1 \setminus \{\mathcal{B}\}$ ,  $\mathcal{L}_2 := \mathcal{L}_2 \cup \{\mathcal{B}\}$ .

Compute  $\tilde{A}$ ,  $\tilde{b}$ , and  $R$  according to  $\mathcal{B}$ .

$\mathcal{EN} := \mathcal{N}$ .

For all  $j \in \mathcal{N}$ .

Solve the LP  $\max\{e^T v : Ry - r^j \delta + Iv = 0; y, \delta, v \geq 0\}$ .

If this LP is unbounded  $\mathcal{EN} := \mathcal{EN} \setminus \{j\}$ .

End for

For all  $j \in \mathcal{EN}$ .

For all  $i \in \mathcal{B}$ .

If  $\mathcal{B}' = (\mathcal{B} \setminus \{i\}) \cup \{j\}$  is feasible and  $\mathcal{B}' \notin \mathcal{L}_1 \cup \mathcal{L}_2$   
then  $\mathcal{L}_1 := \mathcal{L}_1 \cup \mathcal{B}'$ .

End for.

End for.

End while.

Output:  $\mathcal{L}_2$ .

## Example

- There can be exponentially many efficient bfs

- 

$$\begin{array}{lll}
 \min & x_i & i = 1, \dots, n \\
 \min & -x_i & i = 1, \dots, n \\
 \text{subject to} & x_i \leq 1 & i = 1, \dots, n \\
 & -x_i \leq 1 & i = 1, \dots, n.
 \end{array}$$

- $n$  variables,  $m = 2n$  constraints,  $p = 2n$  objective functions
- all  $2^n$  extreme points of the feasible set are efficient

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# Overview

- 1 Multiobjective Linear Programming
  - Formulation and Example
  - Solving MOLPs by Weighted Sums
- 2 Biobjective LPs and Parametric Simplex
  - The Parametric Simplex Algorithm
  - Biobjective Linear Programmes: Example
- 3 Multiobjective Simplex Method
  - A Multiobjective Simplex Algorithm
  - Multiobjective Simplex: Examples

## Example

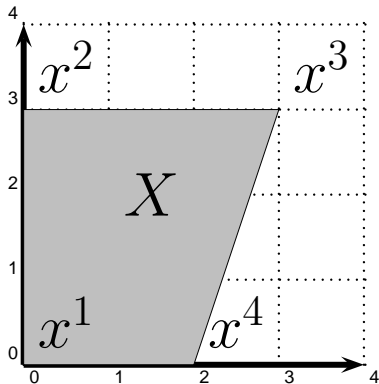
$$\begin{array}{ll} \min & \begin{pmatrix} 3x_1 + x_2 \\ -x_1 - 2x_2 \end{pmatrix} \\ \text{subject to} & x_2 \leq 3 \\ & 3x_1 - x_2 \leq 6 \\ & x \geq 0 \end{array}$$

$LP(\lambda)$

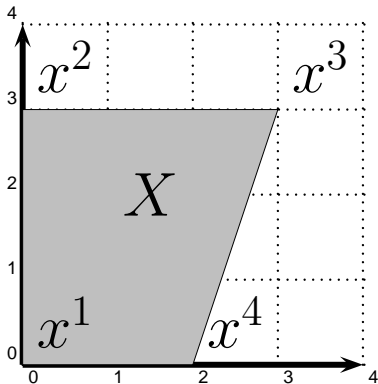
$$\begin{array}{ll} \min & (4\lambda - 1)x_1 + (3\lambda - 2)x_2 \\ \text{subject to} & x_2 + x_3 = 3 \\ & 3x_1 - x_2 + x_4 = 6 \\ & x \geq 0. \end{array}$$



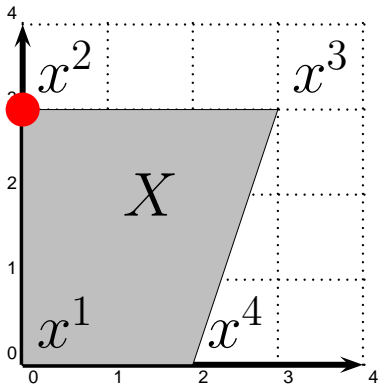
- Phase I: MOLP is feasible  
 $x^0 = (0, 0)$
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- Phase II: First efficient solution  
 $x^2 = (0, 3)$
- Phase III: Efficient entering variables  $s^1, x^2$
- Phase III: Efficient solutions  
 $x^1 = (0, 0), x^3 = (3, 3)$
- Phase III: No more efficient entering variables



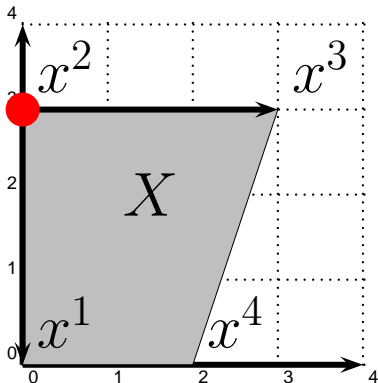
- Phase I: MOLP is feasible  
 $x^0 = (0, 0)$
- Phase II: Optimal weight  
 $\hat{w} = (1, 1)$
- Phase II: First efficient solution  
 $x^2 = (0, 3)$
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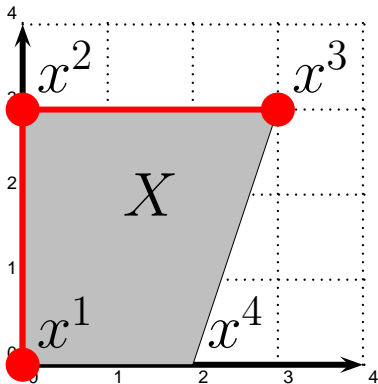
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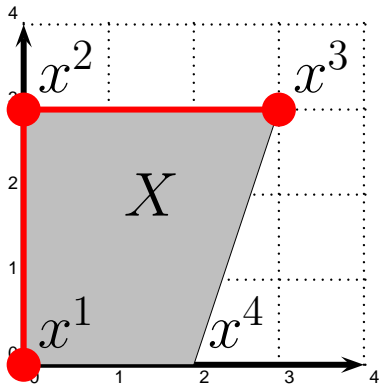
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## Example

$$\begin{array}{llllll} \min & & -x_1 & -2x_2 & & \\ \min & & -x_1 & & +2x_3 & \\ \min & & x_1 & & -x_3 & \\ \text{subject to} & x_1 & +x_2 & & & \leq 1 \\ & & & x_2 & & \leq 2 \\ & x_1 & -x_2 & +x_3 & & \leq 4. \end{array}$$

Slack variables  $x_4, x_5, x_6$  introduced to write the constraints in equality form  $Ax = b$

- Phase I:  $\mathcal{B} = \{4, 5, 6\}$  is a basis with bfs  $x^0 = (0, 0, 0, 1, 2, 4)$
- Phase II:

$$\begin{array}{ll} \min & u_1 + 2u_2 + 4u_3 \\ \text{subject to} & u^T \begin{pmatrix} 1 & 1 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 1 & 0 \\ 1 & -1 & 1 & 0 & 0 & 1 \end{pmatrix} + w^T \begin{pmatrix} -1 & -2 & 0 & 0 & 0 & 0 \\ -1 & 0 & 2 & 0 & 0 & 0 \\ 1 & 0 & -1 & 0 & 0 & 0 \end{pmatrix} \geq 0 \\ & w \geq e \end{array}$$

$$\hat{w} = (1, 1, 1)$$

$$\min\{-x_1 - 2x_2 + x_3 : Ax = b, x \geq 0\}$$

$\mathcal{B}^1 = \{2, 5, 6\}$ ,  $x^1 = (0, 1, 0, 0, 1, 3)$  is efficient bfs,

$$\mathcal{L}_1 = \{\{2, 5, 6\}\}$$



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$$\mathcal{L}_1 = \{\{2, 5, 6\}\}$$

## Phase III

Iteration 1:

$$\mathcal{B}^1 = \{2, 5, 6\}, \mathcal{L}_1 = \emptyset, \mathcal{L}_2 = \{\{2, 5, 6\}\}$$

$\bar{c}^1$	1	0	0	2	0	0	2
$\bar{c}^2$	-1	0	2	0	0	0	0
$\bar{c}^3$	1	0	-1	0	0	0	0
$x_2$	1	1	0	1	0	0	1
$x_5$	-1	0	0	-1	1	0	1
$x_6$	2	0	1	1	0	1	5

$$\mathcal{EN} := \{1, 3, 4\}$$

- Check  $x_1$

1	1	2	-1	0	0	0	0
1	0	2	-1	1	0	0	0
-1	2	0	1	0	1	0	0
1	-1	0	-1	0	0	1	0

LP has optimal solution,  $x_1$  is efficient

- Check  $x_3$

1	1	2	-1	0	0	0	0
1	0	2	0	1	0	0	0
-1	2	0	-2	0	1	0	0
1	-1	0	1	0	0	1	0

LP has optimal solution,  $x_3$  is efficient

- Check  $x_1$

1	1	2	-1	0	0	0	0
1	0	2	-1	1	0	0	0
-1	2	0	1	0	1	0	0
1	-1	0	-1	0	0	1	0

LP has optimal solution,  $x_1$  is efficient

- Check  $x_3$

1	1	2	-1	0	0	0	0
1	0	2	0	1	0	0	0
-1	2	0	-2	0	1	0	0
1	-1	0	1	0	0	1	0

LP has optimal solution,  $x_3$  is efficient

- Check  $x_4$

1	1	2	-2	0	0	0	0
1	0	2	-2	1	0	0	0
-1	2	0	0	0	1	0	0
1	-1	0	0	0	0	1	0

LP is unbounded,  $x_4$  is not efficient

- $\mathcal{EN} = \{1, 3\}$   
Feasible pivot  $x_1$  enters and  $x_2$  leaves: basis  $\mathcal{B}^2 = \{1, 5, 6\}$   
Feasible pivot  $x_3$  enters and  $x_6$  leaves: basis  $\mathcal{B}^3 = \{2, 3, 5\}$   
 $\mathcal{L}_1 := \{\{1, 5, 6\}, \{2, 3, 5\}\}$

- Check  $x_4$

1	1	2	-2	0	0	0	0
1	0	2	-2	1	0	0	0
-1	2	0	0	0	1	0	0
1	-1	0	0	0	0	1	0

LP is unbounded,  $x_4$  is not efficient

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Feasible pivot  $x_1$  enters and  $x_2$  leaves: basis  $\mathcal{B}^2 = \{1, 5, 6\}$   
Feasible pivot  $x_3$  enters and  $x_6$  leaves: basis  $\mathcal{B}^3 = \{2, 3, 5\}$   
 $\mathcal{L}_1 := \{\{1, 5, 6\}, \{2, 3, 5\}\}$

Iteration 2:

$$\mathcal{B}^2 = \{1, 5, 6\} \text{ with BFS } x^2 = (1, 0, 0, 0, 2, 3)$$

$$\mathcal{L}_1 = \{\{2, 3, 5\}\}, \mathcal{L}_2 = \{\{2, 5, 6\}, \{2, 3, 5\}\}$$

$\bar{c}^1$	0	-1	0	1	0	0	1
$\bar{c}^2$	0	1	2	1	0	0	1
$\bar{c}^3$	0	-1	-1	-1	0	0	-1
$x_2$	1	1	0	1	0	0	1
$x_5$	0	1	0	0	1	0	2
$x_6$	0	-2	1	-1	0	1	3

$$\mathcal{EN} = \{2, 3, 4\}$$

- Check  $x_2$ : Leads back to  $\mathcal{B}^1 = (2, 5, 6)$
- Check  $x_3$ :

-1	1	1	-1	0	0	0	0
-1	0	1	0	1	0	0	0
1	2	1	-2	0	1	0	0
-1	-1	-1	1	0	0	1	0

$x_3$  not efficient

- Check  $x_4$

-1	1	1	-1	0	0	0	0
-1	0	1	-1	1	0	0	0
1	2	1	-1	0	1	0	0
-1	-1	-1	1	0	0	1	0

$x_4$  not efficient

- $\mathcal{EN} = \emptyset$



- Check  $x_2$ : Leads back to  $\mathcal{B}^1 = (2, 5, 6)$
- Check  $x_3$ :

-1	1	1	-1	0	0	0	0
-1	0	1	0	1	0	0	0
<span style="border: 1px solid black; padding: 2px;">1</span>	2	1	-2	0	1	0	0
-1	-1	-1	1	0	0	1	0

$x_3$  not efficient

- Check  $x_4$

-1	1	1	-1	0	0	0	0
-1	0	1	-1	1	0	0	0
<span style="border: 1px solid black; padding: 2px;">1</span>	2	1	-1	0	1	0	0
-1	-1	-1	1	0	0	1	0

$x_4$  not efficient

- $\mathcal{EN} = \emptyset$

- Check  $x_2$ : Leads back to  $\mathcal{B}^1 = (2, 5, 6)$
- Check  $x_3$ :

-1	1	1	-1	0	0	0	0
-1	0	1	0	1	0	0	0
1	2	1	-2	0	1	0	0
-1	-1	-1	1	0	0	1	0

$x_3$  not efficient

- Check  $x_4$

-1	1	1	-1	0	0	0	0
-1	0	1	-1	1	0	0	0
1	2	1	-1	0	1	0	0
-1	-1	-1	1	0	0	1	0

$x_4$  not efficient

- $\mathcal{EN} = \emptyset$

- Check  $x_2$ : Leads back to  $\mathcal{B}^1 = (2, 5, 6)$
- Check  $x_3$ :

-1	1	1	-1	0	0	0	0
-1	0	1	0	1	0	0	0
1	2	1	-2	0	1	0	0
-1	-1	-1	1	0	0	1	0

$x_3$  not efficient

- Check  $x_4$

-1	1	1	-1	0	0	0	0
-1	0	1	-1	1	0	0	0
1	2	1	-1	0	1	0	0
-1	-1	-1	1	0	0	1	0

$x_4$  not efficient

- $\mathcal{EN} = \emptyset$

Iteration 3

 $\mathcal{B}^3 = \{2, 3, 5\}$  with bfs  $x^3 = (0, 1, 5, 0, 1, 0)$  $\mathcal{L}_1 = \emptyset$ ,  $\mathcal{L}_2 = \{\{2, 5, 6\}, \{1, 5, 6\}, \{2, 3, 5\}\}$ 

$\bar{c}^1$	1	0	0	2	0	0	2
$\bar{c}^2$	-5	0	0	-2	0	-2	-10
$\bar{c}^3$	3	0	0	1	0	1	5
$x_2$	1	1	0	1	0	0	1
$x_5$	-1	0	0	-1	1	0	1
$x_3$	2	0	1	1	0	1	5

 $\mathcal{EN} = \{1, 4, 6\}$

- Check  $x_1$

-1	1	-1	1	0	0	0	0
1	2	0	-1	1	0	0	0
-5	-2	-2	5	0	1	0	0
3	1	1	-3	0	0	1	0

$x_4$  is not efficient

- Check  $x_4$

-1	1	-1	-1	0	0	0	0
1	2	0	-2	1	0	0	0
-5	-2	-2	2	0	1	0	0
3	1	1	-1	0	0	1	0

$x_4$  is not efficient

- Check  $x_6$ : Leads back to  $\mathcal{B}^1$

- Check  $x_1$

-1	1	-1	1	0	0	0	0
1	2	0	-1	1	0	0	0
-5	-2	-2	5	0	1	0	0
3	1	1	-3	0	0	1	0

$x_4$  is not efficient

- Check  $x_4$

-1	1	-1	-1	0	0	0	0
1	2	0	-2	1	0	0	0
-5	-2	-2	2	0	1	0	0
3	1	1	-1	0	0	1	0

$x_4$  is not efficient

- Check  $x_6$ : Leads back to  $\mathcal{B}^1$

- Check  $x_1$

-1	1	-1	1	0	0	0	0
1	2	0	-1	1	0	0	0
-5	-2	-2	5	0	1	0	0
3	1	1	-3	0	0	1	0

$x_4$  is not efficient

- Check  $x_4$

-1	1	-1	-1	0	0	0	0
1	2	0	-2	1	0	0	0
-5	-2	-2	2	0	1	0	0
3	1	1	-1	0	0	1	0

$x_4$  is not efficient

- Check  $x_6$ : Leads back to  $\mathcal{B}^1$

Iteration 4:  $\mathcal{L}_1 = \emptyset$ , STOP

Output: List of efficient bases

$$\mathcal{B}^1 = \{2, 5, 6\}, \mathcal{B}^2 =$$

$$\{1, 5, 6\}, \mathcal{B}^3 = \{2, 3, 5\}$$

