

# 6.215/6.255J/15.093J/IDS.200J Optimization Methods

## Lecture 4: The Simplex Method II

September 21, 2021

# Today's Lecture

## Outline

- Review - Simplex method
- Dealing with degeneracy
- Revised Simplex method
- The full tableau implementation
- Finding an initial BFS
- The complete algorithm
- Computational efficiency

# Review ...

LO in standard form,  $A$  full row rank, Basis, Reduced costs

$$\begin{array}{ll}\min & \mathbf{c}^T \mathbf{x} \\ \text{s.t.} & \mathbf{Ax} = \mathbf{b} \\ & \mathbf{x} \geq 0\end{array}$$

$\mathbf{x}^T = (\mathbf{x}_B^T, \mathbf{x}_N^T)$ ,  $\mathbf{x}_B$  basic variables,  $\mathbf{x}_N$  non-basic variables

$$\begin{aligned}\mathbf{Ax} &= \mathbf{b}, \quad \mathbf{A} = [\mathbf{B} | \mathbf{N}] \\ \Rightarrow \mathbf{B}\mathbf{x}_B + \mathbf{N}\mathbf{x}_N &= \mathbf{b} \\ \Rightarrow \mathbf{x}_B + \mathbf{B}^{-1}\mathbf{N}\mathbf{x}_N &= \mathbf{B}^{-1}\mathbf{b} \\ \Rightarrow \mathbf{x}_B &= \mathbf{B}^{-1}\mathbf{b} - \mathbf{B}^{-1}\mathbf{N}\mathbf{x}_N\end{aligned}$$

$$\begin{aligned}z &= \mathbf{c}^T \mathbf{x} = \mathbf{c}_B^T \mathbf{x}_B + \mathbf{c}_N^T \mathbf{x}_N \\ &= \mathbf{c}_B^T (\mathbf{B}^{-1}\mathbf{b} - \mathbf{B}^{-1}\mathbf{N}\mathbf{x}_N) + \mathbf{c}_N^T \mathbf{x}_N \\ &= \mathbf{c}_B^T \mathbf{B}^{-1}\mathbf{b} + (\mathbf{c}_N^T - \mathbf{c}_B^T \mathbf{B}^{-1}\mathbf{N})\mathbf{x}_N\end{aligned}$$

$\bar{c}_j = c_j - \mathbf{c}_B^T \mathbf{B}^{-1} \mathbf{A}_j \quad \forall j \in N \quad \text{the relevant reduced costs}$

## Recap ... The Simplex method

- 1 Start with basis  $\mathbf{B} = [\mathbf{A}_{B(1)}, \dots, \mathbf{A}_{B(m)}]$  and a BFS  $\mathbf{x}$ .
- 2 Compute *reduced costs*:  $\bar{c}_j = c_j - \mathbf{c}_B^T \mathbf{B}^{-1} \mathbf{A}_j, \forall j \in N$ 
  - If  $\bar{c}_j \geq 0, \forall j \in N$ ;  $\mathbf{x}$  optimal; stop.
  - Else select  $j : \bar{c}_j < 0$ .
- 3 Compute *basic direction*:  $d_j = 1, \mathbf{d}_B = -\mathbf{B}^{-1} \mathbf{A}_j$ .
  - If  $\mathbf{d}_B \geq 0 \Rightarrow$  cost unbounded; stop
  - Else
- 4 Greedy step-size:  $\theta^* = \min_{1 \leq i \leq m, d_{B(i)} < 0} \frac{x_{B(i)}}{-d_{B(i)}} \doteq \frac{x_{B(\ell)}}{-d_{B(\ell)}}$
- 5 Form a new basis  $\bar{\mathbf{B}}$  by replacing  $\mathbf{A}_{B(\ell)}$  with  $\mathbf{A}_j$ .
- 6 New BFS  $\mathbf{y} = \mathbf{x} + \theta^* \mathbf{d}$ .  $y_j = \theta^*, y_{B(i)} = x_{B(i)} + \theta^* d_{B(i)}, i \neq \ell$ .

# The Simplex method

## Finite Convergence

### Theorem

- $P = \{\mathbf{x} \mid \mathbf{Ax} = \mathbf{b}, \mathbf{x} \geq 0\} \neq \emptyset$
  - Assume that every BFS non-degenerate
- Then:
- Simplex method terminates after a finite number of iterations
  - At termination, we have an optimal basis  $B$  or we have a direction  $\mathbf{d} : \mathbf{Ad} = 0, \mathbf{d} \geq 0, \mathbf{c}^T \mathbf{d} < 0$  and optimal cost is  $-\infty$ .

# The Simplex method

## Degenerate problems

- $\theta^*$  can equal zero (why?)

$\Rightarrow \mathbf{y} = \mathbf{x}$ , although  $\bar{\mathbf{B}} \neq \mathbf{B}$ .

- Even if  $\theta^* > 0$ , there might be a tie for

$$\min_{1 \leq i \leq m, d_{B(i)} < 0} \frac{x_{B(i)}}{-d_{B(i)}}$$

$\Rightarrow$  next BFS degenerate.

- Conclusion: Finite termination not guaranteed; cycling is possible.

# The Simplex method

## Avoiding cycling

- Cycling can be avoided by carefully selecting which variables enter and exit the basis.
- One example:
  - among all variables  $\bar{c}_j < 0$ , pick the smallest subscript;
  - among all variables eligible to exit the basis, pick the one with the smallest subscript.

# Revised Simplex method

## Practical Implementation

- ➊ Start with (feasible) basis  $\mathbf{B} = [\mathbf{A}_{B(1)}, \dots, \mathbf{A}_{B(m)}]$  and  $\mathbf{B}^{-1}$
- ➋ Compute  $\mathbf{p}^T = \mathbf{c}_B^T \mathbf{B}^{-1}$ ,  $\bar{c}_j = c_j - \mathbf{p}^T \mathbf{A}_j$  for all (nonbasic indices)  $j$ .
  - If  $\bar{c}_j \geq 0$  for all  $j$ ;  $\mathbf{x}$  optimal; Stop.
  - Else select  $j : \bar{c}_j < 0$ .
- ➌ Compute  $\mathbf{u} \doteq -\mathbf{d}_B = \mathbf{B}^{-1} \mathbf{A}_j$ . (Note this is just  $u_i = -d_B(i)$ )
  - If  $\mathbf{u} \leq 0 \Rightarrow$  cost unbounded; Stop
  - Else
- ➍  $\theta^* = \min_{1 \leq i \leq m, u_i > 0} \frac{x_{B(i)}}{u_i} \doteq \frac{x_{B(\ell)}}{u_\ell}$
- ➎ Form a new basis  $\bar{\mathbf{B}}$  by replacing  $\mathbf{A}_{B(\ell)}$  with  $\mathbf{A}_j$ .
- ➏  $y_j = \theta^*$ ,  $y_{B(i)} = x_{B(i)} - \theta^* u_i$ ,  $i \neq \ell$ .
- ➐ Efficiently compute  $\bar{\mathbf{B}}^{-1}$  by transforming  $[\mathbf{B}^{-1} | \mathbf{u}]$  into  $[\bar{\mathbf{B}}^{-1} | \mathbf{e}_\ell]$   
(where  $\mathbf{e}_\ell$  is the unit vector in  $\mathbb{R}^m$  with a 1 in its  $\ell^{\text{th}}$  row)



# Revised Simplex

## Step 7: Updating the inverse of a matrix - how?

- Suppose that we start at a BFS with basic indices  $B$  and basis matrix

$$B = [A_{B(1)}, \dots, A_{B(m)}] \quad \text{with inverse} \quad B^{-1}.$$

- We have a simplex iteration in which  $B(\ell)$  leaves in favor of  $j \notin B$ .
- New basic indices  $\bar{B} = (B(1), \dots, B(\ell-1), j, B(\ell+1), \dots, B(m))$  with basis matrix

$$\bar{B} = [A_{B(1)}, \dots, A_{B(\ell-1)}, A_j, A_{B(\ell+1)}, \dots, A_{B(m)}].$$

- How do we compute the inverse of  $\bar{B}$ ?

# Revised Simplex

## Updating the inverse of a matrix - explanation

- It turns out that  $B^{-1}$  is a close approximation to  $\bar{B}^{-1}$ :

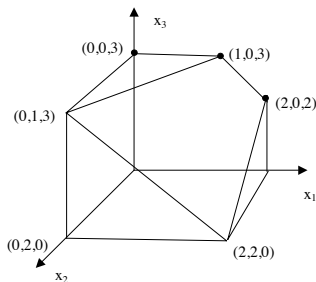
$$B^{-1}\bar{B} = [e_1, \dots, e_{\ell-1}, u, e_{\ell+1}, \dots, e_m]$$

- At most  $m$  “row operations” necessary to transform  $B^{-1}\bar{B}$  into an identity matrix  $I$  (in matrix form this corresponds to finding  $Q$  so that  $QB^{-1}\bar{B} = I$ , which then implies that  $\bar{B}^{-1} = QB^{-1}$ )
- The same row operations convert  $[B^{-1}|u]$  into  $[\bar{B}^{-1}|e_\ell]$

# Revised Simplex

Back to our example

$$\begin{array}{llllll} \min & x_1 + & 5x_2 & -2x_3 & & \\ \text{s.t.} & x_1 + & x_2 + & x_3 & \leq & 4 \\ & x_1 & & & \leq & 2 \\ & & & x_3 & \leq & 3 \\ & & 3x_2 + & x_3 & \leq & 6 \\ & x_1, & x_2, & x_3 & \geq & 0 \end{array}$$



# Revised Simplex

Back to our example

$$B = \{\mathbf{A}_1, \mathbf{A}_3, \mathbf{A}_6, \mathbf{A}_7\}, \quad \text{BFS: } \mathbf{x} = (2, 0, 2, 0, 0, 1, 4)^T$$

$$\mathbf{B} = \begin{bmatrix} 1 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 \\ 0 & 1 & 0 & 1 \end{bmatrix}, \quad \mathbf{B}^{-1} = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 1 & -1 & 0 & 0 \\ -1 & 1 & 1 & 0 \\ -1 & 1 & 0 & 1 \end{bmatrix}$$

$$\bar{\mathbf{c}}^T = (0, 7, 0, 2, -3, 0, 0)$$

$$(u_1, u_2, u_3, u_4)^T = \mathbf{B}^{-1} \mathbf{A}_5 = (1, -1, 1, 1)^T$$

$$\theta^* = \min \left( \frac{2}{1}, \frac{1}{1}, \frac{4}{1} \right) = 1$$

$$\Rightarrow \mathbf{A}_6 \text{ exits the basis } (\ell = 3, B(3) = 6)$$

# Revised Simplex

Back to our example

“...Efficiently compute  $\bar{B}^{-1}$  by transforming  $[B^{-1}|u]$  into  $[\bar{B}^{-1}|e_\ell]$ ...”

$$[B^{-1}|u] = \left[ \begin{array}{cccc|c} 0 & 1 & 0 & 0 & 1 \\ 1 & -1 & 0 & 0 & -1 \\ -1 & 1 & 1 & 0 & 1 \\ -1 & 1 & 0 & 1 & 1 \end{array} \right] \Rightarrow \left[ \begin{array}{cccc|c} 1 & 0 & -1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ -1 & 1 & 1 & 0 & 1 \\ 0 & 0 & -1 & 1 & 0 \end{array} \right]$$

$$\Rightarrow \bar{B}^{-1} = \left[ \begin{array}{cccc} 1 & 0 & -1 & 0 \\ 0 & 0 & 1 & 0 \\ -1 & 1 & 1 & 0 \\ 0 & 0 & -1 & 1 \end{array} \right]$$

# Revised Simplex

Updating the inverse of a matrix - practical issues

- **Numerical Stability**

$B^{-1}$  needs to be computed from scratch once in a while, as errors accumulate

- **Sparsity**

$B^{-1}$  is represented in terms of sparse triangular matrices (LU decomposition).

# Full tableau implementation

Instead of simply maintaining and updating  $\mathbf{B}^{-1}$ , we maintain and update the  $m \times (n + 1)$  matrix  $\mathbf{B}^{-1}[\mathbf{b}|\mathbf{A}]$ , called the simplex tableau.

Augmenting it with a top row (the *zeroth row*), we have:

$-\mathbf{c}_B^T \mathbf{B}^{-1} \mathbf{b}$	$\mathbf{c}^T - \mathbf{c}_B^T \mathbf{B}^{-1} \mathbf{A}$
$\mathbf{B}^{-1} \mathbf{b}$	$\mathbf{B}^{-1} \mathbf{A}$

or, in more detail,

$-\mathbf{c}_B^T \mathbf{x}_B$	$\bar{c}_1$	$\dots$	$\bar{c}_n$
$x_{B(1)}$			
$\vdots$	$\mathbf{B}^{-1} \mathbf{A}_1$	$\dots$	$\mathbf{B}^{-1} \mathbf{A}_n$
$x_{B(m)}$			

# Full tableau implementation

## Example 3.5

$$\begin{array}{ll}\min & -10x_1 - 12x_2 - 12x_3 \\ \text{s.t.} & x_1 + 2x_2 + 2x_3 \leq 20 \\ & 2x_1 + x_2 + 2x_3 \leq 20 \\ & 2x_1 + 2x_2 + x_3 \leq 20 \\ & x_1, x_2, x_3 \geq 0\end{array}$$

$$\begin{array}{llllllll}\min & -10x_1 & -12x_2 & -12x_3 & & & & \\ \text{s.t.} & x_1 + 2x_2 + 2x_3 + x_4 & & & & & & = 20 \\ & 2x_1 + x_2 + 2x_3 & & & + x_5 & & & = 20 \\ & 2x_1 + 2x_2 + x_3 & & & & + x_6 & & = 20 \\ & x_1, \dots, x_6 \geq 0\end{array}$$

BFS:  $\mathbf{x} = (0, 0, 0, 20, 20, 20)^T$

$\mathbf{B} = [\mathbf{A}_4, \mathbf{A}_5, \mathbf{A}_6]$



# Full tableau implementation

## Example 3.5

		$x_1$	$x_2$	$x_3$	$x_4$	$x_5$	$x_6$
	0	-10	-12	-12	0	0	0
$x_4 =$	20	1	2	2	1	0	0
$x_5 =$	20	2*	1	2	0	1	0
$x_6 =$	20	2	2	1	0	0	1

$$\bar{\mathbf{c}}^T = \mathbf{c}^T - \mathbf{c}_B^T \mathbf{B}^{-1} \mathbf{A} = (-10, -12, -12, 0, 0, 0)$$

# Full tableau implementation

## Example 3.5

		$x_1$	$x_2$	$x_3$	$x_4$	$x_5$	$x_6$
	100	0	-7	-2	0	5	0
$x_4 =$	10	0	1.5	1*	1	-0.5	0
$x_1 =$	10	1	0.5	1	0	0.5	0
$x_6 =$	0	0	1	-1	0	-1	1

# Full tableau implementation

## Example 3.5

		$x_1$	$x_2$	$x_3$	$x_4$	$x_5$	$x_6$
	120	0	-4	0	2	4	0
$x_3 =$	10	0	1.5	1	1	-0.5	0
$x_1 =$	0	1	-1	0	-1	1	0
$x_6 =$	10	0	2.5*	0	1	-1.5	1

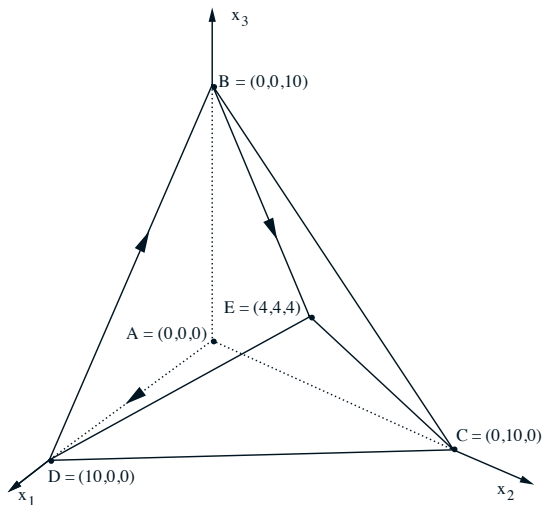
# Full tableau implementation

## Example 3.5

		$x_1$	$x_2$	$x_3$	$x_4$	$x_5$	$x_6$
	136	0	0	0	3.6	1.6	1.6
$x_3 =$	4	0	0	1	0.4	0.4	-0.6
$x_1 =$	4	1	0	0	-0.6	0.4	0.4
$x_2 =$	4	0	1	0	0.4	-0.6	0.4

# Full tableau implementation

## Example 3.5



# Comparison of implementations

	Full tableau	Revised simplex
Memory	$O(mn)$	$O(m^2)$
Worst-case time	$O(mn)$	$O(mn)$
Best-case time	$O(mn)$	$O(m^2)$

# “Back to Square 1”: Finding an initial BFS

- **Goal:** Obtain a BFS of  $\mathbf{Ax} = \mathbf{b}$ ,  $\mathbf{x} \geq 0$  or decide that the problem is infeasible.

- Special case:  $\mathbf{b} \geq 0$ ,  $\mathbf{Ax} \leq \mathbf{b}$ ,  $\mathbf{x} \geq 0$

$$\Rightarrow \mathbf{Ax} + \mathbf{s} = \mathbf{b}, \mathbf{x}, \mathbf{s} \geq 0$$

$$\mathbf{s} = \mathbf{b}, \mathbf{x} = 0$$

# Finding an initial BFS

## Artificial variables

$$\mathbf{Ax} = \mathbf{b}, \mathbf{x} \geq 0$$

- 1 Multiply some rows with  $-1$  to insure  $\mathbf{b} \geq 0$ .
- 2 Introduce artificial variables  $\mathbf{y}$ , start with initial  $\mathbf{y} = \mathbf{b}$ ,  $\mathbf{x} = 0$ , and apply simplex to auxiliary problem

$$\begin{array}{ll}\min & y_1 + y_2 + \dots + y_m \\ \text{s.t.} & \mathbf{Ax} + \mathbf{y} = \mathbf{b} \\ & \mathbf{x}, \mathbf{y} \geq 0\end{array}$$

- 3 If cost  $> 0 \Rightarrow$  **problem infeasible**; stop.
- 4 If cost  $= 0$  and no artificial variable is in the basis, then a BFS was found.
- 5 Else, all  $y_i^* = 0$ , but some are still in the basis. Say we have  $\mathbf{A}_{B(1)}, \dots, \mathbf{A}_{B(k)}$  in basis  $k < m$ . There are  $m - k$  additional columns of  $\mathbf{A}$  to form a basis.



# Finding an initial BFS

## Artificial variables

$$\mathbf{Ax} = \mathbf{b}, \mathbf{x} \geq 0$$

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$$\begin{array}{ll}\min & y_1 + y_2 + \dots + y_m \\ \text{s.t.} & \mathbf{Ax} + \mathbf{y} = \mathbf{b} \\ & \mathbf{x}, \mathbf{y} \geq 0\end{array}$$

- 3 If cost  $> 0 \Rightarrow$  **problem infeasible**; stop.
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- 5 Else, all  $y_i^* = 0$ , but some are still in the basis. Say we have  $\mathbf{A}_{B(1)}, \dots, \mathbf{A}_{B(k)}$  in basis  $k < m$ . There are  $m - k$  additional columns of  $\mathbf{A}$  to form a basis.
- 6 Drive artificial variables out of the basis: If  $\ell$ th basic variable is artificial examine  $\ell$ th row of  $\mathbf{B}^{-1}\mathbf{A}$ . If all elements  $= 0 \Rightarrow$  row redundant. Otherwise pivot with  $\neq 0$  element.

# Finding an initial BFS

## Example 3.8

$$\begin{array}{llllll} \min & x_1 & + & x_2 & + & x_3 & & \\ s.t. & x_1 & + & 2x_2 & + & 3x_3 & & = 3 \\ & -x_1 & + & 2x_2 & + & 6x_3 & & = 2 \\ & & & 4x_2 & + & 9x_3 & & = 5 \\ & & & & & 3x_3 & + & x_4 = 1 \\ & & & & & & & x_1, \dots, x_4 \geq 0. \end{array}$$

# Finding an initial BFS

## Example 3.8

$$\begin{array}{llllll} \min & x_1 & + & x_2 & + & x_3 \\ \text{s.t.} & x_1 & + & 2x_2 & + & 3x_3 & = & 3 \\ & -x_1 & + & 2x_2 & + & 6x_3 & = & 2 \\ & & & 4x_2 & + & 9x_3 & = & 5 \\ & & & & & 3x_3 & + & x_4 & = & 1 \\ & & & & & & & & & x_1, \dots, x_4 \geq 0. \end{array}$$

$$\begin{array}{llllllllll} \min & & & & & & x_5 & + & x_6 & + & x_7 & + & x_8 \\ \text{s.t.} & x_1 & + & 2x_2 & + & 3x_3 & & + & x_5 & & & & = & 3 \\ & -x_1 & + & 2x_2 & + & 6x_3 & & & + & x_6 & & & = & 2 \\ & & & 4x_2 & + & 9x_3 & & & & & + & x_7 & = & 5 \\ & & & & & 3x_3 & + & x_4 & & & & + & x_8 & = & 1 \\ & & & & & & & & & & & & & x_1, \dots, x_8 \geq 0. \end{array}$$

# Finding an initial BFS

## Example 3.8

		$x_1$	$x_2$	$x_3$	$x_4$	$x_5$	$x_6$	$x_7$	$x_8$
	-11	0	-8	-21	-1	0	0	0	0
$x_5 =$	3	1	2	3	0	1	0	0	0
$x_6 =$	2	-1	2	6	0	0	1	0	0
$x_7 =$	5	0	4	9	0	0	0	1	0
$x_8 =$	1	0	0	3	1*	0	0	0	1

		$x_1$	$x_2$	$x_3$	$x_4$	$x_5$	$x_6$	$x_7$	$x_8$
	-10	0	-8	-18	0	0	0	0	1
$x_5 =$	3	1	2	3	0	1	0	0	0
$x_6 =$	2	-1	2	6	0	0	1	0	0
$x_7 =$	5	0	4	9	0	0	0	1	0
$x_4 =$	1	0	0	3*	1	0	0	0	1

# Finding an initial BFS

## Example 3.8

		$x_1$	$x_2$	$x_3$	$x_4$	$x_5$	$x_6$	$x_7$	$x_8$
	-4	0	-8	0	6	0	0	0	7
$x_5 =$	2	1	2	0	-1	1	0	0	-1
$x_6 =$	0	-1	2*	0	-2	0	1	0	-2
$x_7 =$	2	0	4	0	-3	0	0	1	-3
$x_3 =$	1/3	0	0	1	1/3	0	0	0	1/3

		$x_1$	$x_2$	$x_3$	$x_4$	$x_5$	$x_6$	$x_7$	$x_8$
	-4	-4	0	0	-2	0	4	0	-1
$x_5 =$	2	2*	0	0	1	1	-1	0	1
$x_2 =$	0	-1/2	1	0	-1	0	1/2	0	-1
$x_7 =$	2	2	0	0	1	0	-2	1	1
$x_3 =$	1/3	0	0	1	1/3	0	0	0	1/3

# Finding an initial BFS

## Example 3.8

		$x_1$	$x_2$	$x_3$	$x_4$	$x_5$	$x_6$	$x_7$	$x_8$
	0	0	0	0	0	2	2	0	1
$x_1 =$	1	1	0	0	$1/2$	$1/2$	$-1/2$	0	$1/2$
$x_2 =$	$1/2$	0	1	0	$-3/4$	$1/4$	$1/4$	0	$-3/4$
$x_7 =$	0	0	0	0	0	-1	-1	1	0
$x_3 =$	$1/3$	0	0	1	$1/3$	0	0	0	$1/3$

		$x_1$	$x_2$	$x_3$	$x_4$
	*	*	*	*	*
$x_1 =$	1	1	0	0	$1/2$
$x_2 =$	$1/2$	0	1	0	$-3/4$
$x_3 =$	$1/3$	0	0	1	$1/3$

# A complete algorithm for LO

## Phase I:

- 1 By multiplying some of the constraints by  $-1$ , change the problem so that  $\mathbf{b} \geq 0$ .
- 2 Introduce  $y_1, \dots, y_m$ , if necessary, and apply the simplex method to  $\min \sum_{i=1}^m y_i$ .
- 3 If  $\text{cost} > 0$ , original problem is infeasible; STOP.
- 4 If  $\text{cost} = 0$ , a feasible solution to the original problem has been found.
- 5 Drive artificial variables out of the basis, potentially eliminating redundant rows.

# A complete algorithm for LO

## Phase II:

- 1 Let the final basis and tableau obtained from Phase I be the initial basis and tableau for Phase II.
- 2 Compute the reduced costs of all variables for this initial basis, using the cost coefficients of the original problem.
- 3 Apply the simplex method to the original problem.



# A complete algorithm for LO

## Possible outcomes

- 1 Infeasible: Detected at Phase I.
- 2 **A** has linearly dependent rows: Detected at Phase I, eliminate redundant rows.
- 3 Unbounded ( $\text{cost} = -\infty$ ): detected at Phase II.
- 4 Optimal solution: Terminate at Phase II in optimality check.

# The big- $M$ method

An alternative method

- Similar but with a different cost function to start with ... combines the two phases into one:

$$\begin{array}{ll}\min & \sum_{j=1}^n c_j x_j + M \sum_{i=1}^m y_i \\ \text{s.t.} & \mathbf{Ax} + \mathbf{y} = \mathbf{b} \\ & \mathbf{x}, \mathbf{y} \geq 0\end{array}$$

- $M$  needs to be chosen carefully ...

# Computational efficiency of the simplex method

Exceptional practical behavior: linear in  $m$  or  $n$

Worst case?

# Computational efficiency of the simplex method

Exceptional practical behavior: linear in  $m$  or  $n$

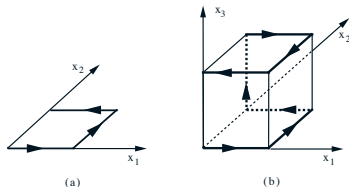
Worst case?

Consider

$$\begin{array}{ll}\max & x_n \\ \text{s.t.} & \epsilon \leq x_1 \leq 1 \\ & \epsilon x_{i-1} \leq x_i \leq 1 - \epsilon x_{i-1}, \quad i = 2, \dots, n\end{array}$$

# Computational efficiency

worst case



# Computational efficiency

## Theorem

- *The feasible set has  $2^n$  vertices*
- *The vertices can be ordered so that each one is adjacent to and has lower cost than the previous one.*
- *There exists a pivoting rule under which the simplex method requires  $2^n - 1$  changes of basis before it terminates.*