## Linear Programming

Lecture 6: The Simplex Algorithm Language, Notation, and Linear Algebra

- Dictionaries for LPs in Standard Form
- 2 The Simplex Algorithm via Matrix Multiplication
- 3 The Block Structure of the Simplex Algorithm
- 4 Block Structure and Matrix Multiplication
- 5 The Block Structure of an Optimal Tableau
- 6 Block Structure and Duality

$$\mathcal{P}: \ \ \mathsf{maximize} \ \ c^{\mathsf{T}}x$$
 
$$\mathsf{subject to} \ \ Ax \leq b$$
 
$$0 \leq x \ ,$$
 
$$\mathsf{where} \ c \in \mathbb{R}^n, \ b \in \mathbb{R}^m, \ A \in \mathbb{R}^{m \times n}$$

$$\mathcal{P}: \ \text{maximize} \ c^{T}x$$
 
$$\text{subject to} \ Ax \leq b$$
 
$$0 \leq x \ ,$$
 where  $c \in \mathbb{R}^{n}, \ b \in \mathbb{R}^{m}, \ A \in \mathbb{R}^{m \times n}$ 

$$\label{eq:constraints} \begin{array}{ll} \mathcal{P}: & \text{maximize} & c^T x \\ & \text{subject to} & Ax \leq b \\ & 0 \leq x \ , \end{array} \qquad \left[ \sum_{j=1}^n a_{ij} x_j \leq b_i, \ i=1,\ldots,m \right]$$

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

slack variables 
$$x_{n+i} := b_i - \sum_{j=1}^n a_{ij}x_j$$
  $i = 1, 2, ..., m$ 

$$\begin{array}{ll} \mathcal{P}: & \text{maximize} & c^Tx \\ & \text{subject to} & \mathcal{A}x \leq b \\ & 0 \leq x \ , \end{array} \qquad \left[ \sum_{j=1}^n a_{ij} x_j \leq b_i, \ i=1,\ldots,m \right]$$

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

slack variables 
$$x_{n+i} := b_i - \sum_{j=1}^n a_{ij}x_j$$
  $i = 1, 2, ..., m$ 

objective 
$$z := \sum_{j=1}^{n} c_j x_j$$

$$\begin{array}{ll} \mathcal{P}: & \text{maximize} & c^Tx \\ & \text{subject to} & Ax \leq b \\ & 0 \leq x \ , \end{array} \qquad \left[ \sum_{j=1}^n a_{ij} x_j \leq b_i, \ i=1,\ldots,m \right]$$

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

slack variables 
$$x_{n+i}:=b_i-\sum_{j=1}^n a_{ij}x_j$$
  $i=1,2,\ldots,m$  objective  $z:=\sum_{i=1}^n c_ix_i$ 

A dictionary for  $\mathcal P$  is any system of the form

$$x_i = \widehat{b}_i - \sum_{j \in N} \widehat{a}_{ij} x_j$$
  $i \in B$   $(D_B)$ 
 $z = \widehat{z} + \sum_{j \in N} \widehat{c}_j x_j$ 

A dictionary for  ${\mathcal P}$  is any system of the form

$$x_i = \widehat{b}_i - \sum_{j \in N} \widehat{a}_{ij} x_j$$
  $i \in B$   $(D_B)$   $z = \widehat{z} + \sum_{j \in N} \widehat{c}_j x_j$ 

where B and N are index sets partitioning  $\{1, \ldots, n+m\}$  and satisfying

A dictionary for  ${\mathcal P}$  is any system of the form

$$x_{i} = \widehat{b}_{i} - \sum_{j \in N} \widehat{a}_{ij} x_{j} \qquad i \in B$$

$$z = \widehat{z} + \sum_{i \in I} \widehat{c}_{j} x_{j} \qquad (D_{B})$$

where B and N are index sets partitioning  $\{1,\ldots,n+m\}$  and satisfying

(1) B contains m elements and N contains n elements,

A dictionary for  ${\mathcal P}$  is any system of the form

$$x_i = \hat{b}_i - \sum_{j \in N} \hat{a}_{ij} x_j$$
  $i \in B$   $(D_B)$ 
 $z = \hat{z} + \sum_{j \in N} \hat{c}_j x_j$ 

where B and N are index sets partitioning  $\{1,\ldots,n+m\}$  and satisfying

- (1) B contains m elements and N contains n elements,
- (2)  $B \cap N = \emptyset$

A dictionary for  $\mathcal{P}$  is any system of the form

$$x_i = \hat{b}_i - \sum_{j \in N} \hat{a}_{ij} x_j$$
  $i \in B$   $(D_B)$ 
 $z = \hat{z} + \sum_{j \in N} \hat{c}_j x_j$ 

where B and N are index sets partitioning  $\{1, \ldots, n+m\}$  and satisfying

- (1) B contains m elements and N contains n elements,
- (2)  $B \cap N = \emptyset$
- (3)  $B \cup N = \{1, 2, ..., n + m\},\$

A dictionary for  ${\mathcal P}$  is any system of the form

$$x_i = \hat{b}_i - \sum_{j \in N} \widehat{a}_{ij} x_j$$
  $i \in B$   $(D_B)$ 

$$z = \widehat{z} + \sum_{j \in N} \widehat{c}_j x_j$$

where B and N are index sets partitioning  $\{1, \ldots, n+m\}$  and satisfying

- (1) B contains m elements and N contains n elements,
- (2)  $B \cap N = \emptyset$
- (3)  $B \cup N = \{1, 2, ..., n + m\},\$

and such that the systems  $(D_I)$  and  $(D_B)$  have identical solution sets.

$$x_{i} = \widehat{b}_{i} - \sum_{j \in N} \widehat{a}_{ij} x_{j} \qquad i \in B$$

$$z = \widehat{z} + \sum_{j \in N} \widehat{c}_{j} x_{j} \qquad (D_{B})$$

•  $B \sim$  basic variables  $N \sim$  nonbasic variables

$$x_i = \widehat{b}_i - \sum_{j \in N} \widehat{a}_{ij} x_j$$
  $i \in B$   $(D_B)$ 

$$z = \widehat{z} + \sum_{j \in N} \widehat{c}_j x_j$$

- $B \sim \text{basic variables}$   $N \sim \text{nonbasic variables}$
- Basic solution identified by the dictionary is

$$x_i = \hat{b}_i$$
  $i \in B$   
 $x_j = 0$   $j \in N$ .

$$x_i = \widehat{b}_i - \sum_{j \in N} \widehat{a}_{ij} x_j$$
  $i \in B$   $(D_B)$   $z = \widehat{z} + \sum_{j \in N} \widehat{c}_j x_j$ 

- $B \sim \text{basic variables}$   $N \sim \text{nonbasic variables}$
- Basic solution identified by the dictionary is

$$x_i = \hat{b}_i$$
  $i \in B$   
 $x_j = 0$   $j \in N$ .

• Dictionary is feasible if  $0 \le \hat{b}_i$  for  $i \in B$ .

$$x_i = \widehat{b}_i - \sum_{j \in N} \widehat{a}_{ij} x_j$$
  $i \in B$   $(D_B)$ 

$$z = \widehat{z} + \sum_{i \in N} \widehat{c}_i x_i$$

- $B \sim \text{basic variables}$   $N \sim \text{nonbasic variables}$
- Basic solution identified by the dictionary is

$$x_i = \hat{b}_i$$
  $i \in B$   
 $x_j = 0$   $j \in N$ .

- Dictionary is feasible if  $0 \le \hat{b}_i$  for  $i \in B$ .
- If feasible, then the basic solution is a basic feasible solution (BFS).

$$x_i = \widehat{b}_i - \sum_{j \in N} \widehat{a}_{ij} x_j$$
  $i \in B$   $(D_B)$ 

$$z = \widehat{z} + \sum_{i \in N} \widehat{c}_i x_i$$

- $B \sim \text{basic variables}$   $N \sim \text{nonbasic variables}$
- Basic solution identified by the dictionary is

$$x_i = \widehat{b}_i$$
  $i \in B$   
 $x_j = 0$   $j \in N$ .

- Dictionary is feasible if  $0 \le \hat{b}_i$  for  $i \in B$ .
- If feasible, then the basic solution is a basic feasible solution (BFS).
- A feasible dictionary is *optimal* if  $\hat{c}_j \leq 0$   $j \in N$ .

We have already seen that Gaussian elimination can be performed by matrix multiplication.

We have already seen that Gaussian elimination can be performed by matrix multiplication.

How does this look in the context of the simplex algorithm?

We have already seen that Gaussian elimination can be performed by matrix multiplication.

How does this look in the context of the simplex algorithm?

First recall that

$$\begin{bmatrix} I_{s\times s} & -\alpha^{-1}a & 0 \\ 0 & \alpha^{-1} & 0 \\ 0 & -\alpha^{-1}b & I_{t\times t} \end{bmatrix} \begin{pmatrix} a \\ \alpha \\ b \end{pmatrix} = \begin{bmatrix} a-a \\ \alpha^{-1}\alpha \\ -b+b \end{bmatrix} = \begin{pmatrix} 0 \\ 1 \\ 0 \end{pmatrix}.$$

We have already seen that Gaussian elimination can be performed by matrix multiplication.

How does this look in the context of the simplex algorithm?

First recall that

$$\begin{bmatrix} I_{s\times s} & -\alpha^{-1}a & 0 \\ 0 & \alpha^{-1} & 0 \\ 0 & -\alpha^{-1}b & I_{t\times t} \end{bmatrix} \begin{pmatrix} a \\ \alpha \\ b \end{pmatrix} = \begin{bmatrix} a-a \\ \alpha^{-1}\alpha \\ -b+b \end{bmatrix} = \begin{pmatrix} 0 \\ 1 \\ 0 \end{pmatrix}.$$

The elimination matrix and its inverse.

$$G = \begin{bmatrix} I_{s \times s} & -\alpha^{-1} a & 0 \\ 0 & \alpha^{-1} & 0 \\ 0 & -\alpha^{-1} b & I_{t \times t} \end{bmatrix} \qquad G^{-1} = \begin{bmatrix} I & a & 0 \\ 0 & \alpha & 0 \\ 0 & b & I \end{bmatrix}$$

The elimination matrices also have the following important property.

$$\begin{bmatrix} I_{s \times s} & -\alpha^{-1}a & 0 \\ 0 & \alpha^{-1} & 0 \\ 0 & -\alpha^{-1}b & I_{t \times t} \end{bmatrix} \begin{pmatrix} x \\ 0 \\ y \end{pmatrix} = \begin{pmatrix} x \\ 0 \\ y \end{pmatrix}$$

The elimination matrices also have the following important property.

$$\begin{bmatrix} I_{s \times s} & -\alpha^{-1} a & 0 \\ 0 & \alpha^{-1} & 0 \\ 0 & -\alpha^{-1} b & I_{t \times t} \end{bmatrix} \begin{pmatrix} x \\ 0 \\ y \end{pmatrix} = \begin{pmatrix} x \\ 0 \\ y \end{pmatrix}$$

We call these matrices *Gauss-Jordan elimination* or pivot matrices.

The elimination matrices also have the following important property.

$$\begin{bmatrix} I_{s \times s} & -\alpha^{-1} a & 0 \\ 0 & \alpha^{-1} & 0 \\ 0 & -\alpha^{-1} b & I_{t \times t} \end{bmatrix} \begin{pmatrix} x \\ 0 \\ y \end{pmatrix} = \begin{pmatrix} x \\ 0 \\ y \end{pmatrix}$$

We call these matrices *Gauss-Jordan elimination* or pivot matrices.

These matices perform precisely the operations required in order to execute a simplex pivot.

The elimination matrices also have the following important property.

$$\begin{bmatrix} I_{s \times s} & -\alpha^{-1} a & 0 \\ 0 & \alpha^{-1} & 0 \\ 0 & -\alpha^{-1} b & I_{t \times t} \end{bmatrix} \begin{pmatrix} x \\ 0 \\ y \end{pmatrix} = \begin{pmatrix} x \\ 0 \\ y \end{pmatrix}$$

We call these matrices Gauss-Jordan elimination or pivot matrices.

These matices perform precisely the operations required in order to execute a simplex pivot.

Each simplex pivot can be realized as left multiplication of the simplex tableau by the appropriate Gaussian-Jordan pivot matrix.

1	4	2	1	0	0	11
3	2	1	0	1	0	5
4	2	2	0	0	1	8
4	5	3	0	0	0	0

$$\begin{bmatrix} 1 & -2 & 0 & 0 \\ 0 & \frac{1}{2} & 0 & 0 \\ 0 & -1 & 1 & 0 \\ 0 & \frac{-5}{2} & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 4 & 2 & 1 & 0 & 0 & 11 \\ 3 & 2 & 1 & 0 & 1 & 0 & 5 \\ 4 & 2 & 2 & 0 & 0 & 1 & 8 \\ \hline 4 & 5 & 3 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$\begin{bmatrix} 1 & -2 & 0 & 0 \\ 0 & \frac{1}{2} & 0 & 0 \\ 0 & -1 & 1 & 0 \\ 0 & \frac{-5}{2} & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 4 & 2 & 1 & 0 & 0 & 11 \\ 3 & 2 & 1 & 0 & 1 & 0 & 5 \\ 4 & 2 & 2 & 0 & 0 & 1 & 8 \\ 4 & 5 & 3 & 0 & 0 & 0 & 0 \end{bmatrix} = \begin{bmatrix} -5 & 0 & 0 & 1 & -2 & 0 & 1 \\ \frac{3}{2} & 1 & \frac{1}{2} & 0 & \frac{1}{2} & 0 & \frac{5}{2} \\ 1 & 0 & 1 & 0 & -1 & 1 & 3 \\ -\frac{7}{2} & 0 & \frac{1}{2} & 0 & \frac{-5}{2} & 0 & \frac{-25}{2} \end{bmatrix}$$

$$\begin{bmatrix} 1 & -2 & 0 & 0 \\ 0 & \frac{1}{2} & 0 & 0 \\ 0 & -1 & 1 & 0 \\ 0 & \frac{-5}{2} & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 4 & 2 & 1 & 0 & 0 & 11 \\ 3 & 2 & 1 & 0 & 1 & 0 & 5 \\ 4 & 2 & 2 & 0 & 0 & 1 & 8 \\ \hline 4 & 5 & 3 & 0 & 0 & 0 & 0 \end{bmatrix} = \begin{bmatrix} -5 & 0 & 0 & 1 & -2 & 0 & 1 \\ \frac{3}{2} & 1 & \frac{1}{2} & 0 & \frac{1}{2} & 0 & \frac{5}{2} \\ 1 & 0 & 1 & 0 & -1 & 1 & 3 \\ \hline -\frac{7}{2} & 0 & \frac{1}{2} & 0 & \frac{-5}{2} & 0 & \frac{-25}{2} \end{bmatrix}$$

$$\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & \frac{-1}{2} & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & \frac{-1}{2} & 1 \end{bmatrix} \begin{bmatrix} -5 & 0 & 0 & 1 & -2 & 0 & 1 \\ \frac{3}{2} & 1 & \frac{1}{2} & 0 & \frac{1}{2} & 0 & \frac{5}{2} \\ 1 & 0 & 1 & 0 & -1 & 1 & 3 \\ \frac{-7}{2} & 0 & \frac{1}{2} & 0 & \frac{-5}{2} & 0 & \frac{-25}{2} \end{bmatrix}$$

$$\begin{bmatrix} 1 & -2 & 0 & 0 \\ 0 & \frac{1}{2} & 0 & 0 \\ 0 & -1 & 1 & 0 \\ 0 & \frac{-5}{2} & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 4 & 2 & 1 & 0 & 0 & 11 \\ 3 & 2 & 1 & 0 & 1 & 0 & 5 \\ 4 & 2 & 2 & 0 & 0 & 1 & 8 \\ \hline 4 & 5 & 3 & 0 & 0 & 0 & 0 \end{bmatrix} = \begin{bmatrix} -5 & 0 & 0 & 1 & -2 & 0 & 1 \\ \frac{3}{2} & 1 & \frac{1}{2} & 0 & \frac{1}{2} & 0 & \frac{5}{2} \\ 1 & 0 & 1 & 0 & -1 & 1 & 3 \\ \hline -\frac{7}{2} & 0 & \frac{1}{2} & 0 & \frac{-25}{2} & 0 & \frac{-25}{2} \end{bmatrix}$$

$$\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & \frac{-1}{2} & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & \frac{-1}{2} & 1 \end{bmatrix} \begin{bmatrix} -5 & 0 & 0 & 1 & -2 & 0 & 1 \\ \frac{3}{2} & 1 & \frac{1}{2} & 0 & \frac{1}{2} & 0 & \frac{5}{2} \\ 1 & 0 & 1 & 0 & -1 & 1 & 3 \\ \frac{-7}{2} & 0 & \frac{1}{2} & 0 & \frac{-5}{2} & 0 & \frac{-25}{2} \end{bmatrix} = \begin{bmatrix} -5 & 0 & 0 & 1 & -2 & 0 & 1 \\ 1 & 1 & 0 & 0 & 1 & \frac{-1}{2} & 1 \\ 1 & 0 & 1 & 0 & -1 & 1 & 3 \\ -4 & 0 & 0 & 0 & -2 & \frac{-1}{2} & -14 \end{bmatrix}$$

$$\begin{bmatrix} A & I & b \\ \hline c^{\mathsf{T}} & 0 & 0 \end{bmatrix}$$

$$G_2G_1\left[\begin{array}{c|cc}A & I & b\\\hline c^{\mathsf{T}} & 0 & 0\end{array}\right]$$

$$G_2G_1\begin{bmatrix} A & I & b \\ \hline c^T & 0 & 0 \end{bmatrix}$$

where

$$G_2G_1 = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & \frac{-1}{2} & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & \frac{-1}{2} & 1 \end{bmatrix} \begin{bmatrix} 1 & -2 & 0 & 0 \\ 0 & \frac{1}{2} & 0 & 0 \\ 0 & -1 & 1 & 0 \\ 0 & \frac{-5}{2} & 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 & -2 & 0 & 0 \\ 0 & 1 & \frac{-1}{2} & 0 \\ 0 & -1 & 1 & 0 \\ 0 & -2 & \frac{-1}{2} & 1 \end{bmatrix}$$

$$G_2G_1\left[\begin{array}{c|cc}A&I&b\\\hline c^{\mathsf{T}}&0&0\end{array}\right]$$

## The Simplex Algorithm via Matrix Multiplication

$$G_2G_1\begin{bmatrix} A & I & b \\ \hline c^T & 0 & 0 \end{bmatrix}$$

$$= \begin{bmatrix} 1 & -2 & 0 & 0 \\ 0 & 1 & \frac{-1}{2} & 0 \\ 0 & -1 & 1 & 0 \\ 0 & -2 & \frac{-1}{2} & 1 \end{bmatrix} \begin{bmatrix} 1 & 4 & 2 & 1 & 0 & 0 & | & 11 \\ 3 & 2 & 1 & 0 & 1 & 0 & | & 5 \\ 4 & 2 & 2 & 0 & 0 & 1 & | & 8 \\ \hline 4 & 5 & 3 & 0 & 0 & 0 & | & 0 \end{bmatrix}$$

# The Simplex Algorithm via Matrix Multiplication

$$G_2G_1\begin{bmatrix} A & I & b \\ \hline c^T & 0 & 0 \end{bmatrix}$$

$$= \begin{bmatrix} 1 & -2 & 0 & 0 \\ 0 & 1 & \frac{-1}{2} & 0 \\ 0 & -1 & 1 & 0 \\ 0 & -2 & \frac{-1}{2} & 1 \end{bmatrix} \begin{bmatrix} 1 & 4 & 2 & 1 & 0 & 0 & | & 11 \\ 3 & 2 & 1 & 0 & 1 & 0 & | & 5 \\ 4 & 2 & 2 & 0 & 0 & 1 & | & 8 \\ \hline 4 & 5 & 3 & 0 & 0 & 0 & | & 0 \end{bmatrix}$$

$$= \begin{bmatrix} -5 & 0 & 0 & 1 & -2 & 0 & | & 1 \\ 1 & 1 & 0 & 0 & 1 & \frac{-1}{2} & | & 1 \\ 1 & 0 & 1 & 0 & -1 & 1 & | & 3 \\ \hline -4 & 0 & 0 & 0 & -2 & \frac{-1}{2} & | & -14 \end{bmatrix}$$

Let  $T_0$  be the initial tableau:

$$\mathcal{T}_0 = \left[ egin{array}{cc|c} 0 & A & I & b \ -1 & c^{\scriptscriptstyle\mathsf{T}} & 0 & 0 \end{array} 
ight] \; .$$

Let  $T_0$  be the initial tableau:

$$\mathcal{T}_0 = \left[ egin{array}{cc|c} 0 & A & I & b \ -1 & c^{\mathsf{T}} & 0 & 0 \end{array} 
ight] \; .$$

Let  $T_k$  denote the tableau after k pivots:

$$T_k = \left[ \begin{array}{cc|c} 0 & \widehat{A} & R & \widehat{b} \\ -1 & \widehat{c}^{\mathsf{T}} & -y^{\mathsf{T}} & \widehat{z} \end{array} \right]$$

Let  $T_0$  be the initial tableau:

$$\mathcal{T}_0 = \left[ egin{array}{cc|c} 0 & A & I & b \ -1 & c^{\scriptscriptstyle\mathsf{T}} & 0 & 0 \end{array} 
ight] \; .$$

Let  $T_k$  denote the tableau after k pivots:

$$T_k = \left[ \begin{array}{cc|c} 0 & \widehat{A} & R & \widehat{b} \\ -1 & \widehat{c}^{\mathsf{T}} & -y^{\mathsf{T}} & \widehat{z} \end{array} \right]$$

 $T_k$  is obtained from  $T_0$  by multiplying it on the left by a product of Gaussian pivot matrices  $G := G_k G_{k-1} \cdots G_1$ :

$$GT_0 = T_k$$

where *G* is invertible  $(G^{-1} = G_1^{-1}G_2^{-1} \cdots G_k^{-1})$ .



Let's investigate the structure of  $T_k$  by examining the consequence of this product in terms of the block structure of  $T_0$  and  $T_k$ .

$$T_0 = \left[ \begin{array}{cc|c} 0 & A & I & b \\ -1 & c^{\mathsf{T}} & 0 & 0 \end{array} \right] \qquad T_k = \left[ \begin{array}{cc|c} 0 & \widehat{A} & R & \widehat{b} \\ -1 & \widehat{c}^{\mathsf{T}} & -y^{\mathsf{T}} & \widehat{z} \end{array} \right]$$

Here we use the fact that the first column of the simplex tableau remains unchanged by pivoting.

Let's investigate the structure of  $T_k$  by examining the consequence of this product in terms of the block structure of  $T_0$  and  $T_k$ .

$$T_0 = \left[ \begin{array}{cc|c} 0 & A & I & b \\ -1 & c^{\mathsf{T}} & 0 & 0 \end{array} \right] \qquad T_k = \left[ \begin{array}{cc|c} 0 & \widehat{A} & R & \widehat{b} \\ -1 & \widehat{c}^{\mathsf{T}} & -y^{\mathsf{T}} & \widehat{z} \end{array} \right]$$

Here we use the fact that the first column of the simplex tableau remains unchanged by pivoting.

First we must decompose G into a block structure that is conformal to that of  $T_0$ :

Let's investigate the structure of  $T_k$  by examining the consequence of this product in terms of the block structure of  $T_0$  and  $T_k$ .

$$T_{0} = \left[ \begin{array}{cc|c} 0 & A & I & b \\ -1 & c^{\mathsf{T}} & 0 & 0 \end{array} \right] \qquad T_{k} = \left[ \begin{array}{cc|c} 0 & \widehat{A} & R & \widehat{b} \\ -1 & \widehat{c}^{\mathsf{T}} & -y^{\mathsf{T}} & \widehat{z} \end{array} \right]$$

Here we use the fact that the first column of the simplex tableau remains unchanged by pivoting.

First we must decompose G into a block structure that is conformal to that of  $T_0$ :

$$G = \left[ \begin{array}{cc} M & u \\ v^{\mathsf{T}} & \beta \end{array} \right],$$

where  $M \in \mathbb{R}^{m \times m}$ ,  $u, v \in \mathbb{R}^m$ , and  $\beta \in \mathbb{R}$ .

$$\begin{bmatrix} 0 & \widehat{A} & R & | \widehat{b} \\ -1 & \widehat{c}^{\mathsf{T}} & -y^{\mathsf{T}} & | \widehat{z} \end{bmatrix} = T_k$$

$$\begin{bmatrix} 0 & \widehat{A} & R & | \widehat{b} \\ -1 & \widehat{c}^{\mathsf{T}} & -y^{\mathsf{T}} & | \widehat{z} \end{bmatrix} = T_k = GT_0$$

$$\begin{bmatrix} 0 & \widehat{A} & R & \widehat{b} \\ -1 & \widehat{c}^{\mathsf{T}} & -y^{\mathsf{T}} & \widehat{z} \end{bmatrix} = T_k = GT_0$$

$$= \begin{bmatrix} M & u \\ v^{\mathsf{T}} & \beta \end{bmatrix} \begin{bmatrix} 0 & A & I & b \\ -1 & c^{\mathsf{T}} & 0 & 0 \end{bmatrix}$$

$$\begin{bmatrix} 0 & \widehat{A} & R & \widehat{b} \\ -1 & \widehat{c}^{\mathsf{T}} & -y^{\mathsf{T}} & \widehat{z} \end{bmatrix} = T_k = GT_0$$

$$= \begin{bmatrix} M & u \\ v^{\mathsf{T}} & \beta \end{bmatrix} \begin{bmatrix} 0 & A & I & b \\ -1 & c^{\mathsf{T}} & 0 & 0 \end{bmatrix}$$

$$= \begin{bmatrix} -u & MA + uc^{\mathsf{T}} & M & Mb \\ -\beta & v^{\mathsf{T}}A + \beta c^{\mathsf{T}} & v^{\mathsf{T}} & v^{\mathsf{T}}b \end{bmatrix}.$$

$$\begin{bmatrix} 0 & \widehat{A} & R & \widehat{b} \\ -1 & \widehat{c}^{\mathsf{T}} & -y^{\mathsf{T}} & \widehat{z} \end{bmatrix} = \begin{bmatrix} -u & MA + uc^{\mathsf{T}} & M & Mb \\ -\beta & v^{\mathsf{T}}A + \beta c^{\mathsf{T}} & v^{\mathsf{T}} & v^{\mathsf{T}} \end{bmatrix}$$

$$\begin{bmatrix} 0 & \widehat{A} & R & \widehat{b} \\ -1 & \widehat{c}^{\mathsf{T}} & -y^{\mathsf{T}} & \widehat{z} \end{bmatrix} = \begin{bmatrix} -u & MA + uc^{\mathsf{T}} & M & Mb \\ -\beta & v^{\mathsf{T}}A + \beta c^{\mathsf{T}} & v^{\mathsf{T}} & v^{\mathsf{T}} \end{bmatrix}$$

$$\begin{bmatrix} 0 & \widehat{A} & R & \widehat{b} \\ -1 & \widehat{c}^{\mathsf{T}} & -y^{\mathsf{T}} & \widehat{z} \end{bmatrix} = \begin{bmatrix} -u & MA + uc^{\mathsf{T}} & M & Mb \\ -\beta & v^{\mathsf{T}}A + \beta c^{\mathsf{T}} & v^{\mathsf{T}} & v^{\mathsf{T}} \end{bmatrix}$$

$$u = 0$$

$$\left[\begin{array}{cc|c} 0 & \widehat{A} & R & \widehat{b} \\ -1 & \widehat{c}^{\mathsf{T}} & -y^{\mathsf{T}} & \widehat{z} \end{array}\right] = \left[\begin{array}{cc|c} -u & MA + uc^{\mathsf{T}} & M & Mb \\ -\beta & v^{\mathsf{T}}A + \beta c^{\mathsf{T}} & v^{\mathsf{T}} & v^{\mathsf{T}} \end{array}\right]$$

$$u = 0$$
  $\beta = 1$ 

$$\begin{bmatrix} 0 & \widehat{A} & R & \widehat{b} \\ -1 & \widehat{c}^{\mathsf{T}} & -y^{\mathsf{T}} & \widehat{z} \end{bmatrix} = \begin{bmatrix} -u & MA + uc^{\mathsf{T}} & M & Mb \\ -\beta & v^{\mathsf{T}}A + \beta c^{\mathsf{T}} & v^{\mathsf{T}} & v^{\mathsf{T}} \end{bmatrix}$$

$$u = 0$$
  $\beta = 1$   $M = R$ 

$$\begin{bmatrix} 0 & \widehat{A} & R & \widehat{b} \\ -1 & \widehat{c}^{\mathsf{T}} & -y^{\mathsf{T}} & \widehat{z} \end{bmatrix} = \begin{bmatrix} -u & MA + uc^{\mathsf{T}} & M & Mb \\ -\beta & v^{\mathsf{T}}A + \beta c^{\mathsf{T}} & v^{\mathsf{T}} & v^{\mathsf{T}} \end{bmatrix}$$

$$u = 0$$
  $\beta = 1$   $M = R$  and  $v = -y$ .

$$\begin{bmatrix} 0 & \widehat{A} & R & \widehat{b} \\ -1 & \widehat{c}^{\mathsf{T}} & -y^{\mathsf{T}} & \widehat{z} \end{bmatrix} = \begin{bmatrix} -u & MA + uc^{\mathsf{T}} & M & Mb \\ -\beta & v^{\mathsf{T}}A + \beta c^{\mathsf{T}} & v^{\mathsf{T}} & v^{\mathsf{T}} \end{bmatrix}$$

Equating terms on the left and right gives

$$u = 0$$
  $\beta = 1$   
 $M = R$  and  $v = -y$ .

Therefore,

$$T_k = \left[ \begin{array}{cc|c} R & 0 \\ -y^\mathsf{\scriptscriptstyle T} & 1 \end{array} \right] \left[ \begin{array}{cc|c} 0 & A & I & b \\ -1 & c^\mathsf{\scriptscriptstyle T} & 0 & 0 \end{array} \right] = \left[ \begin{array}{cc|c} 0 & RA & R & Rb \\ -1 & c^\mathsf{\scriptscriptstyle T} - y^\mathsf{\scriptscriptstyle T} A & -y^\mathsf{\scriptscriptstyle T} & -y^\mathsf{\scriptscriptstyle T} b \end{array} \right] \; ,$$

where the matrix R is necessarily invertible.

$$\left[\begin{array}{cc|c} 0 & \widehat{A} & R & \widehat{b} \\ -1 & \widehat{c}^{\mathsf{T}} & -y^{\mathsf{T}} & \widehat{z} \end{array}\right] = \left[\begin{array}{cc|c} -u & MA + uc^{\mathsf{T}} & M & Mb \\ -\beta & v^{\mathsf{T}}A + \beta c^{\mathsf{T}} & v^{\mathsf{T}} & v^{\mathsf{T}} \end{array}\right]$$

Equating terms on the left and right gives

$$u = 0$$
  $\beta = 1$   $M = R$  and  $v = -y$ .

Therefore,

$$T_k = \left[ \begin{array}{cc|c} R & 0 \\ -y^\mathsf{\scriptscriptstyle T} & 1 \end{array} \right] \left[ \begin{array}{cc|c} 0 & A & I & b \\ -1 & c^\mathsf{\scriptscriptstyle T} & 0 & 0 \end{array} \right] = \left[ \begin{array}{cc|c} 0 & RA & R & Rb \\ -1 & c^\mathsf{\scriptscriptstyle T} - y^\mathsf{\scriptscriptstyle T} A & -y^\mathsf{\scriptscriptstyle T} & -y^\mathsf{\scriptscriptstyle T} b \end{array} \right] \; ,$$

where the matrix R is necessarily invertible. ( $R \sim$ record matrix)

$$T_k = \left[ \begin{array}{cc|c} R & 0 \\ -y^\mathsf{\scriptscriptstyle T} & 1 \end{array} \right] \left[ \begin{array}{cc|c} 0 & A & I & b \\ -1 & c^\mathsf{\scriptscriptstyle T} & 0 & 0 \end{array} \right] = \left[ \begin{array}{cc|c} 0 & RA & R & Rb \\ -1 & c^\mathsf{\scriptscriptstyle T} - y^\mathsf{\scriptscriptstyle T} A & -y^\mathsf{\scriptscriptstyle T} & -y^\mathsf{\scriptscriptstyle T} b \end{array} \right]$$

We say that  $T_k$  is an *optimal tableau* if the simplex algorithm terminates at this tableau.

$$T_k = \left[ \begin{array}{cc|c} R & 0 \\ -y^\mathsf{\scriptscriptstyle T} & 1 \end{array} \right] \left[ \begin{array}{cc|c} 0 & A & I & b \\ -1 & c^\mathsf{\scriptscriptstyle T} & 0 & 0 \end{array} \right] = \left[ \begin{array}{cc|c} 0 & RA & R & Rb \\ -1 & c^\mathsf{\scriptscriptstyle T} - y^\mathsf{\scriptscriptstyle T} A & -y^\mathsf{\scriptscriptstyle T} & -y^\mathsf{\scriptscriptstyle T} b \end{array} \right]$$

We say that  $T_k$  is an *optimal tableau* if the simplex algorithm terminates at this tableau.

That is,  $T_k$  is an optimal tableau if and only if

$$T_k = \left[ \begin{array}{cc|c} R & 0 \\ -y^\mathsf{\scriptscriptstyle T} & 1 \end{array} \right] \left[ \begin{array}{cc|c} 0 & A & I & b \\ -1 & c^\mathsf{\scriptscriptstyle T} & 0 & 0 \end{array} \right] = \left[ \begin{array}{cc|c} 0 & RA & R & Rb \\ -1 & c^\mathsf{\scriptscriptstyle T} - y^\mathsf{\scriptscriptstyle T} A & -y^\mathsf{\scriptscriptstyle T} & -y^\mathsf{\scriptscriptstyle T} b \end{array} \right]$$

We say that  $T_k$  is an *optimal tableau* if the simplex algorithm terminates at this tableau.

That is,  $T_k$  is an optimal tableau if and only if

• it is feasible:  $0 \le Rb$ , and

$$T_k = \left[ \begin{array}{cc|c} R & 0 \\ -y^\mathsf{\scriptscriptstyle T} & 1 \end{array} \right] \left[ \begin{array}{cc|c} 0 & A & I & b \\ -1 & c^\mathsf{\scriptscriptstyle T} & 0 & 0 \end{array} \right] = \left[ \begin{array}{cc|c} 0 & RA & R & Rb \\ -1 & c^\mathsf{\scriptscriptstyle T} - y^\mathsf{\scriptscriptstyle T} A & -y^\mathsf{\scriptscriptstyle T} & -y^\mathsf{\scriptscriptstyle T} b \end{array} \right]$$

We say that  $T_k$  is an *optimal tableau* if the simplex algorithm terminates at this tableau.

That is,  $T_k$  is an optimal tableau if and only if

- it is feasible:  $0 \le Rb$ , and
- the z-row has non-positive entries:

$$c - A^{\mathsf{T}} y \le 0$$
 or equivalently  $A^{\mathsf{T}} y \ge c$   
 $-y \le 0$  or equivalently  $0 \le y$ .

$$T_k = \left[ \begin{array}{cc|c} R & 0 \\ -y^\mathsf{\scriptscriptstyle T} & 1 \end{array} \right] \left[ \begin{array}{cc|c} 0 & A & I & b \\ -1 & c^\mathsf{\scriptscriptstyle T} & 0 & 0 \end{array} \right] = \left[ \begin{array}{cc|c} 0 & RA & R & Rb \\ -1 & c^\mathsf{\scriptscriptstyle T} - y^\mathsf{\scriptscriptstyle T} A & -y^\mathsf{\scriptscriptstyle T} & -y^\mathsf{\scriptscriptstyle T} b \end{array} \right]$$

We say that  $T_k$  is an *optimal tableau* if the simplex algorithm terminates at this tableau.

That is,  $T_k$  is an optimal tableau if and only if

- it is feasible:  $0 \le Rb$ , and
- the z-row has non-positive entries:

$$c - A^{\mathsf{T}} y \le 0$$
 or equivalently  $A^{\mathsf{T}} y \ge c$   
 $-y \le 0$  or equivalently  $0 \le y$ .

In this case the optimal value  $= z = b^{\mathsf{T}}y$ .

$$\begin{bmatrix}
0 & RA & R & Rb \\
-1 & c^{\mathsf{T}} - y^{\mathsf{T}}A & -y^{\mathsf{T}} & -y^{\mathsf{T}}b
\end{bmatrix}$$

$$\left[\begin{array}{cc|c}
0 & RA & R & Rb \\
-1 & c^{\mathsf{T}} - y^{\mathsf{T}}A & -y^{\mathsf{T}} & -y^{\mathsf{T}}b
\end{array}\right]$$

$$0\leq \textit{Rb},$$

$$\left[\begin{array}{cc|c} 0 & RA & R & Rb \\ -1 & c^{\mathsf{T}} - y^{\mathsf{T}}A & -y^{\mathsf{T}} & -y^{\mathsf{T}}b \end{array}\right]$$

$$0 \leq Rb, \quad A^{\mathsf{T}}y \geq c,$$

$$\left[\begin{array}{cc|c} 0 & RA & R & Rb \\ -1 & c^{\mathsf{T}} - y^{\mathsf{T}}A & -y^{\mathsf{T}} & -y^{\mathsf{T}}b \end{array}\right]$$

$$0 \leq Rb, \quad A^{\scriptscriptstyle\mathsf{T}} y \geq c, \quad 0 \leq y,$$

$$\left[\begin{array}{cc|c} 0 & RA & R & Rb \\ -1 & c^{\mathsf{T}} - y^{\mathsf{T}}A & -y^{\mathsf{T}} & -y^{\mathsf{T}}b \end{array}\right]$$

$$0 \leq Rb, \quad A^{\mathsf{T}}y \geq c, \quad 0 \leq y, \quad c^{\mathsf{T}}x^* = z = b^{\mathsf{T}}y,$$

$$\left[\begin{array}{cc|c} 0 & RA & R & Rb \\ -1 & c^{\mathsf{T}} - y^{\mathsf{T}}A & -y^{\mathsf{T}} & -y^{\mathsf{T}}b \end{array}\right]$$

with

$$0 \leq Rb, \quad A^{\mathsf{T}}y \geq c, \quad 0 \leq y, \quad c^{\mathsf{T}}x^* = z = b^{\mathsf{T}}y,$$

where  $x^*$  is the optimal solution to

$$\mathcal{P} \quad \text{max} \quad c^{\mathsf{T}} x \\ \text{s.t.} \quad Ax \leq b \\ 0 \leq x$$

$$\left[\begin{array}{cc|c} 0 & RA & R & Rb \\ -1 & c^{\mathsf{T}} - y^{\mathsf{T}}A & -y^{\mathsf{T}} & -y^{\mathsf{T}}b \end{array}\right]$$

with

$$0 \le Rb$$
,  $A^{\mathsf{T}}y \ge c$ ,  $0 \le y$ ,  $c^{\mathsf{T}}x^* = z = b^{\mathsf{T}}y$ ,

where  $x^*$  is the optimal solution to

$$\left[\begin{array}{cc|c} 0 & RA & R & Rb \\ -1 & c^{\mathsf{T}} - y^{\mathsf{T}}A & -y^{\mathsf{T}} & -y^{\mathsf{T}}b \end{array}\right]$$

with

$$0 \le Rb$$
,  $A^{\mathsf{T}}y \ge c$ ,  $0 \le y$ ,  $c^{\mathsf{T}}x^* = z = b^{\mathsf{T}}y$ ,

where  $x^*$  is the optimal solution to

WEAK DUALITY THM.  $\Rightarrow$  Y SOLVES  $\mathcal{D}$  !!!

## Optimal Tableaus Yield Optimal Solutions

**Theorem:**[Optimal Tableau Theorem] If the simplex tableau

$$\begin{bmatrix}
0 & RA & R & Rb \\
-1 & c^{\mathsf{T}} - y^{\mathsf{T}}A & -y^{\mathsf{T}} & -y^{\mathsf{T}}b
\end{bmatrix}$$

is optimal for  $\mathcal{P}$ , i.e. if  $x^*$  is the associated BFS and

$$0 \le Rb$$
,  $A^{\mathsf{T}}y \ge c$ ,  $0 \le y$ ,  $c^{\mathsf{T}}x^* = z = b^{\mathsf{T}}y$ ,

then  $x^*$  is an optimal solution to  $\mathcal{P}$  and y is an optimal solution to  $\mathcal{D}$ .



## Plastic Cup Factory Reprised

$$\begin{array}{ll} \mathcal{P} & \text{maximize} & 25B + 20\,\textit{C} \\ & \text{subject to} & 20B + 12\,\textit{C} \leq 1800 \\ & & \frac{1}{15}\,\textit{B} + \frac{1}{15}\,\textit{C} \leq 8 \\ & & 0 \leq \textit{B},\,\textit{C} \\ \end{array}$$

## Plastic Cup Factory Reprised

$$\begin{array}{ll} \mathcal{P} & \text{maximize} & 25B+20\textit{C} \\ & \text{subject to} & 20B+12\textit{C} \leq 1800 \\ & & \frac{1}{15}B+\frac{1}{15}\textit{C} \leq 8 \\ & & 0 \leq \textit{B}, \textit{C} \\ \end{array}$$

$$\mathcal{D}$$
 minimize  $1800R + 8L$   
subject to  $20R + \frac{1}{15}L \ge 25$   
 $12R + \frac{1}{15}L \ge 20$   
 $0 < R, L$ 

$$\begin{array}{ll} \mathcal{P} & \text{maximize} & 25B+20\textit{C} \\ & \text{subject to} & 20B+12\textit{C} \leq 1800 \\ & & \frac{1}{15}\textit{B} + \frac{1}{15}\textit{C} \leq 8 \\ & & 0 \leq \textit{B}, \textit{C} \\ \end{array}$$

$$\begin{bmatrix} 20 & 12 & 1 & 0 & 1800 \\ \frac{1}{15} & \frac{1}{15} & 0 & 1 & 8 \\ 25 & 20 & 0 & 0 & 0 \end{bmatrix}$$

$$\mathcal{D}$$
 minimize  $1800R + 8L$  subject to  $20R + \frac{1}{15}L \ge 25$   $12R + \frac{1}{15}L \ge 20$   $0 \le R, L$ 

$$\mathcal{P}$$
 max  $4x_1 + 5x_2 + 3x_3$   
s.t.  $x_1 + 4x_2 + 2x_3 \le 11$   
 $3x_1 + 2x_2 + x_3 \le 5$   
 $4x_1 + 2x_2 + 2x_3 \le 8$   
 $0 < x_1, x_2, x_3$ 

$$\mathcal{P}$$
 max  $4x_1 + 5x_2 + 3x_3$   
s.t.  $x_1 + 4x_2 + 2x_3 \le 11$   
 $3x_1 + 2x_2 + x_3 \le 5$   
 $4x_1 + 2x_2 + 2x_3 \le 8$   
 $0 \le x_1, x_2, x_3$ 

$$\mathcal{D} \quad \text{min} \quad 11y_1 + 5y_2 + 8y_3 \\ \text{s.t.} \quad y_1 + 3y_2 + 4y_3 & \geq 4 \\ 4y_1 + 2y_2 + 2y_3 & \geq 5 \\ 2y_1 + y_2 + 2y_3 & \geq 3 \\ 0 < y_1, y_2, y_3$$

$$T_0 = \begin{bmatrix} 1 & 4 & 2 & 1 & 0 & 0 & | & 11 \\ 3 & 2 & 1 & 0 & 1 & 0 & | & 5 \\ 4 & 2 & 2 & 0 & 0 & 1 & | & 8 \\ \hline 4 & 5 & 3 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$T_0 = \begin{bmatrix} 1 & 4 & 2 & 1 & 0 & 0 & | & 11 \\ 3 & 2 & 1 & 0 & 1 & 0 & | & 5 \\ 4 & 2 & 2 & 0 & 0 & 1 & | & 8 \\ \hline 4 & 5 & 3 & 0 & 0 & 0 & | & 0 \end{bmatrix}$$

$$T_0 = \begin{bmatrix} 1 & 4 & 2 & 1 & 0 & 0 & | & 11 \\ 3 & 2 & 1 & 0 & 1 & 0 & | & 5 \\ 4 & 2 & 2 & 0 & 0 & 1 & | & 8 \\ \hline 4 & 5 & 3 & 0 & 0 & 0 & | & 0 \end{bmatrix} \Rightarrow$$

$$T_0 = \begin{bmatrix} 1 & 4 & 2 & 1 & 0 & 0 & | & 11 \\ 3 & 2 & 1 & 0 & 1 & 0 & | & 5 \\ 4 & 2 & 2 & 0 & 0 & 1 & | & 8 \\ \hline 4 & 5 & 3 & 0 & 0 & 0 & | & 0 \end{bmatrix} \Rightarrow$$

$$T_{\text{opt}} = \begin{bmatrix} -5 & 0 & 0 & 1 & -2 & 0 & 1\\ 1 & 1 & 0 & 0 & 1 & \frac{-1}{2} & 1\\ 1 & 0 & 1 & 0 & -1 & 1 & 3\\ \hline -4 & 0 & 0 & 0 & -2 & \frac{-1}{2} & -14 \end{bmatrix}$$

$$T_0 = \begin{bmatrix} 1 & 4 & 2 & 1 & 0 & 0 & | & 11 \\ 3 & 2 & 1 & 0 & 1 & 0 & | & 5 \\ 4 & 2 & 2 & 0 & 0 & 1 & | & 8 \\ \hline 4 & 5 & 3 & 0 & 0 & 0 & | & 0 \end{bmatrix} \Rightarrow$$

$$T_{\text{opt}} = \begin{bmatrix} -5 & 0 & 0 & 1 & -2 & 0 & 1\\ 1 & 1 & 0 & 0 & 1 & \frac{-1}{2} & 1\\ 1 & 0 & 1 & 0 & -1 & 1 & 3\\ \hline -4 & 0 & 0 & 0 & -2 & \frac{-1}{2} & -14 \end{bmatrix}$$

$$x^* = (0, 1, 3), \quad y^* = (0, 2, 1/2), \quad z^* = 14$$

#### Check

$$x^* = (0,1,3), \quad y^* = (0,2,1/2), \quad z^* = 14$$

# Strong Duality

If we can now show that the simplex algorithm works, then we have an algorithm that simultaneously solves both the primal and dual problems.

# Strong Duality

If we can now show that the simplex algorithm works, then we have an algorithm that simultaneously solves both the primal and dual problems.

Moreover, the optimal value in the primal and dual coincides giving equality in the weak duality inequality.

# Strong Duality

If we can now show that the simplex algorithm works, then we have an algorithm that simultaneously solves both the primal and dual problems.

Moreover, the optimal value in the primal and dual coincides giving equality in the weak duality inequality.

We now focus on the details of the simplex algorithm to determine if and when it works.

# More Tableau Terminology

#### The block structure formula for simplex tableaus.

$$T_k = \left[ \begin{array}{cc|c} R & 0 \\ -y^\mathsf{\scriptscriptstyle T} & 1 \end{array} \right] \left[ \begin{array}{cc|c} 0 & A & I & b \\ -1 & c^\mathsf{\scriptscriptstyle T} & 0 & 0 \end{array} \right] = \left[ \begin{array}{cc|c} 0 & RA & R & Rb \\ -1 & c^\mathsf{\scriptscriptstyle T} - y^\mathsf{\scriptscriptstyle T} A & -y^\mathsf{\scriptscriptstyle T} & -y^\mathsf{\scriptscriptstyle T} b \end{array} \right]$$

 $T_k$  is primal feasible if  $Rb \ge 0$ .

 $T_k$  is dual feasible if  $0 \le y$  and  $A^T y \ge c$ .

 $T_k$  is optimal if it is both primal and dual feasible in which case  $(x^*, y)$  is a Primal-Dual optimal pair where  $x^*$  is the BFS associated with  $T_k$ . Moreover, the optimal value of the Primal equals that of the Dual.