

## The Simplex Method in Matrix Notation

This is also known as “the Revised Simplex Method”. Matrix Notation gives . . .

1. Conceptual clarity on stuff we know;
2. Computational accuracy and efficiency; and
3. Streamlined access to some new material (like sensitivity analysis).

**Setup—Standard Equality-Style Problem.** A matrix  $A \in \mathbb{R}^{m \times n}$  is given, along with vectors  $\mathbf{b} \in \mathbb{R}^m$ ,  $c \in \mathbb{R}^n$ .

$$(P) \quad \max \{ \mathbf{c}^T \mathbf{x} : A\mathbf{x} = \mathbf{b}, \mathbf{x} \geq 0 \}.$$

Always assume  $A$  has linearly independent rows. This requires  $m \leq n$ .

**Geometric Interpretation.** Label the  $n$  columns of matrix  $A$ :

$$A = \left[ \mathbf{a}^{(1)} \mid \mathbf{a}^{(2)} \mid \cdots \mid \mathbf{a}^{(n)} \right].$$

Given some  $\mathbf{x} \in \mathbb{R}^n$ , recognize

$$A\mathbf{x} = \left[ \mathbf{a}^{(1)} \mid \mathbf{a}^{(2)} \mid \cdots \mid \mathbf{a}^{(n)} \right] \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} = x_1 \mathbf{a}^{(1)} + x_2 \mathbf{a}^{(2)} + \cdots + x_n \mathbf{a}^{(n)}.$$

That’s a *linear combination of cols from A*. So, “Solve for  $x$  in  $A\mathbf{x} = \mathbf{b}$ ” means, “Express the given vector  $\mathbf{b}$  as a linear combination of the cols in  $A$ .” Each col is in  $\mathbb{R}^m$ , and we have  $n$  cols to choose between (with  $n \geq m$ ). For a *basic solution*, pick any  $m$  lin indep cols, call them the basis (truly a basis for  $\mathbb{R}^m$ , the space containing the given rhs  $\mathbf{b}$ ), and use only those. That’s a “basic solution (BS) for  $A\mathbf{x} = \mathbf{b}$ ”; there may be several of these.

Each component  $c_j$  in vector  $c \in \mathbb{R}^n$  tells the reward (if  $c_j > 0$ ) or penalty (if  $c_j < 0$ ) for including column  $\mathbf{a}^{(j)}$  in the representation.

**Simplex Dictionary.** Pick any  $m$  linearly independent columns from  $A$ . Record their subscripts in a set  $\mathcal{B}$ . Call these the basis. Permute/clump selected cols into square matrix  $B$  (size  $m \times m$ ). Symbolic decomposition

$$A \stackrel{\text{def}}{=} [A_{\mathcal{B}} \mid A_{\mathcal{N}}] \stackrel{\text{def}}{=} [B \mid N], \quad \mathbf{x} \stackrel{\text{def}}{=} \begin{bmatrix} \mathbf{x}_{\mathcal{B}} \\ \mathbf{x}_{\mathcal{N}} \end{bmatrix}, \quad c \stackrel{\text{def}}{=} \begin{bmatrix} \mathbf{c}_{\mathcal{B}} \\ \mathbf{c}_{\mathcal{N}} \end{bmatrix},$$

leads to

$$A\mathbf{x} = \mathbf{b} \iff B\mathbf{x}_{\mathcal{B}} = \mathbf{b} - N\mathbf{x}_{\mathcal{N}} \iff \mathbf{x}_{\mathcal{B}} = B^{-1}\mathbf{b} - B^{-1}N\mathbf{x}_{\mathcal{N}}.$$

Track the objective:

$$\begin{aligned} f = \mathbf{c}^T \mathbf{x} &= \mathbf{c}_{\mathcal{B}}^T \mathbf{x}_{\mathcal{B}} + \mathbf{c}_{\mathcal{N}}^T \mathbf{x}_{\mathcal{N}} = \mathbf{c}_{\mathcal{B}}^T (B^{-1}\mathbf{b} - B^{-1}N\mathbf{x}_{\mathcal{N}}) + \mathbf{c}_{\mathcal{N}}^T \mathbf{x}_{\mathcal{N}} \\ &= \mathbf{c}_{\mathcal{B}}^T B^{-1}\mathbf{b} - (\mathbf{c}_{\mathcal{B}}^T B^{-1}N - \mathbf{c}_{\mathcal{N}}^T) \mathbf{x}_{\mathcal{N}}. \end{aligned}$$

New dictionary

$$\frac{f = \mathbf{c}_{\mathcal{B}}^T B^{-1}\mathbf{b} - (\mathbf{c}_{\mathcal{B}}^T B^{-1}N - \mathbf{c}_{\mathcal{N}}^T) \mathbf{x}_{\mathcal{N}}}{\mathbf{x}_{\mathcal{B}} = B^{-1}\mathbf{b} - B^{-1}N\mathbf{x}_{\mathcal{N}}.}$$

. . . an algebraic structure containing symbols  $x_1, \dots, x_n, f$  together with a bunch of numbers. Substituting  $\mathbf{x}_{\mathcal{N}} = \mathbf{0}$  determines the numerical values of  $\mathbf{x}_{\mathcal{B}}^* = B^{-1}\mathbf{b}$  in a Basic Solution for  $A\mathbf{x} = \mathbf{b}$ . It’s nice when this is feasible, but the derivation above does not require that.

**Versatility.** Imagine picking any values at all for the  $n - m$  elements of vector  $\mathbf{x}_{\mathcal{N}}$ . This dictionary shows the  $m$  components of  $\mathbf{x}_{\mathcal{B}}$  you must use to satisfy  $A\mathbf{x} = \mathbf{b}$  and the value of  $f = \mathbf{c}^T \mathbf{x}$  that results when you do. (Feasibility is ignored.) Choosing  $\mathbf{x}_{\mathcal{N}}^* = \mathbf{0}$  gives the basic solution  $\mathbf{x}_{\mathcal{B}}^* = B^{-1}\mathbf{b}$  and the objective value  $f^* = \mathbf{c}^T \mathbf{x}^* = \mathbf{c}_{\mathcal{B}}^T \mathbf{x}_{\mathcal{B}}^* = \mathbf{c}_{\mathcal{B}}^T B^{-1}\mathbf{b}$ .

**Optimality and Improvability.** Suppose  $\mathbf{x}_{\mathcal{B}}^* \geq 0$ , so  $\mathbf{x}^*$  is feasible. Consider the row vector  $\mathbf{z}_{\mathcal{N}}^T = (\mathbf{c}_{\mathcal{B}}^T B^{-1}N - \mathbf{c}_{\mathcal{N}}^T)$ :

- If each component  $z_i > 0$ , every nonzero vector  $x_{\mathcal{N}}$  will subtract a positive amount from  $f^*$ . So  $\mathbf{x}^*$  is the unique maximizer.
- If each component  $z_i \geq 0$ , no nonzero vector  $\mathbf{x}_{\mathcal{N}}$  can add a positive amount to  $f^*$ . So  $x^*$  is a maximizer, but perhaps not unique.
- If some component  $z_k < 0$ , a positive value of component  $(x_{\mathcal{N}})_k$  will make  $f$  increase. Improvement is possible, so we will pivot.

**Pivot Selection.** Suppose we have a feasible dictionary and the cost coefficient row  $\mathbf{z}_{\mathcal{N}}^T = (\mathbf{c}_{\mathcal{B}}^T B^{-1}N - \mathbf{c}_{\mathcal{N}}^T)$  has a negative entry. Identify the associated column of  $A$  and call it  $\mathbf{a}^{(E)}$ . Notice  $E \in \mathcal{N}$ . Choosing  $\mathbf{x}_{\mathcal{N}}(t)$  so that  $x_E = t$  and  $x_j = 0$  for all other  $j \in \mathcal{N}$  leads to  $N\mathbf{x}_{\mathcal{N}}(t) = t\mathbf{a}^{(E)}$ . Track the values of current basic coeffs:

$$\mathbf{x}_{\mathcal{B}}(t) = B^{-1}\mathbf{b} - B^{-1}[t\mathbf{a}^{(E)}]. \quad (**)$$

For many  $t$  this will have  $m$  nonzero entries. Pick the smallest  $t \geq 0$  where one or more entry changes to 0: those entries identify the columns eligible to leave. Call the lucky value  $t^*$ .

**Update.** Swap entering col into basis; your chosen leaving col out; update coefficient vector using  $\mathbf{x}_E^* = t^*$ , other coeffs from (\*\*).

**Efficient Implementation.** One never actually computes  $B^{-1}$  from  $B$ . (Sometimes  $B^{-1}$  is given on exams.) Instead, we solve linear systems as follows:

- (i) To generate objective coefficients, introduce  $y$  to reorganize

$$\mathbf{c}_{\mathcal{B}}^T B^{-1}N = \mathbf{y}^T N, \quad \text{as} \quad \mathbf{y}^T = \mathbf{c}_{\mathcal{B}}^T B^{-1}, \quad \text{i.e.,} \quad \mathbf{y}^T B = \mathbf{c}_{\mathcal{B}}^T.$$

Find  $\mathbf{y}$  by solving a linear system.

- (ii) In coefficient update, find  $\mathbf{d} = B^{-1}\mathbf{a}^{(E)}$  by solving system

$$B\mathbf{d} = \mathbf{a}^{(E)}.$$

Use tiny labels called “basis headers” to remember which cols are basic in each iteration. [Chvátal box 7.1, page 103.]

## The Revised Simplex Method, Step by Step

**Context.** The Revised Simplex Method works on problems of this form:

$$\text{(EqLP)} \quad \max \{ \mathbf{c}^T \mathbf{x} : A\mathbf{x} = \mathbf{b}, \mathbf{x} \geq \mathbf{0} \}.$$

(Many problems can be put into this form.) Here a matrix  $A$  of shape  $m \times n$  is given, along with (column) vectors  $\mathbf{c} \in \mathbb{R}^n$ ,  $\mathbf{b} \in \mathbb{R}^m$ . We assume that  $A$  has linearly independent rows (so  $m \leq n$ ).

**Initialize.** You need a feasible basis to get started. (Try to guess one; use an auxiliary “Phase One” step if guessing fails.) Let  $\mathcal{B}$  be the set of  $m$  subscripts that define the current basis; let  $\mathcal{N}$  be the set containing the  $n - m$  non-basic subscripts.

**Partition.** Use the sets of subscripts  $\mathcal{B}$  and  $\mathcal{N}$  to select columns from  $A$  and their corresponding rows of  $\mathbf{x}$ ,  $\mathbf{c}$ :

$$A = [A_{\mathcal{B}} \quad A_{\mathcal{N}}] = [B \quad N], \quad \mathbf{c} = \begin{bmatrix} \mathbf{c}_{\mathcal{B}} \\ \mathbf{c}_{\mathcal{N}} \end{bmatrix}, \quad \mathbf{x} = \begin{bmatrix} \mathbf{x}_{\mathcal{B}} \\ \mathbf{x}_{\mathcal{N}} \end{bmatrix}.$$

Matrix  $B$  has shape  $m \times m$ . It is certain to be invertible because the columns of  $A$  with indices in  $\mathcal{B}$  must be linearly independent. The dictionary is

$$\frac{f = \mathbf{c}_{\mathcal{B}}^T B^{-1} \mathbf{b} - (\mathbf{c}_{\mathcal{B}}^T B^{-1} N - \mathbf{c}_{\mathcal{N}}^T) \mathbf{x}_{\mathcal{N}}}{\mathbf{x}_{\mathcal{B}} = \quad B^{-1} \mathbf{b} - \quad \quad \quad B^{-1} N \mathbf{x}_{\mathcal{N}}}$$

The current BFS  $\mathbf{x}^* \in \mathbb{R}^n$  has blocks  $\mathbf{x}_{\mathcal{B}}^* = B^{-1} \mathbf{b} \in \mathbb{R}^m$ ,  $\mathbf{x}_{\mathcal{N}}^* = \mathbf{0} \in \mathbb{R}^{n-m}$ .

**Select Entering Col.** Scan  $\mathbf{z}_{\mathcal{N}}^T = \mathbf{c}_{\mathcal{B}}^T B^{-1} N - \mathbf{c}_{\mathcal{N}}^T$  for negative entries. To find  $\mathbf{z}_{\mathcal{N}}$ ,

- (i) Find  $\mathbf{y}^T = \mathbf{c}_{\mathcal{B}}^T B^{-1}$  (a row vector) by solving the system  $\mathbf{y}^T B = \mathbf{c}_{\mathcal{B}}^T$ .
- (ii) Build  $\mathbf{z}_{\mathcal{N}}^T = \mathbf{y}^T N - \mathbf{c}_{\mathcal{N}}^T$ .

If no entry is negative, current BFS is optimal. Stop. If negative entries exist, pick one. It labels a suitable “entering column” which has an original index  $E$ . The column itself is  $\mathbf{a}^{(E)}$ , with coefficient  $x_E$ .

**Select Leaving Col.** Set nonbasic coefficient  $x_E = t$ , while keeping all other nonbasic vars at 0. This gives the vector  $\mathbf{x}_{\mathcal{N}} = \mathbf{x}_{\mathcal{N}}(t)$  exactly one nonzero entry, with

$$N \mathbf{x}_{\mathcal{N}}(t) = t \mathbf{a}^{(E)}.$$

Watch the coefficients of the current basis change as  $t \geq 0$  increases:

$$\mathbf{x}_{\mathcal{B}}(t) = \mathbf{x}_{\mathcal{B}}(0) - B^{-1} N \mathbf{x}_{\mathcal{N}}(t) = \mathbf{x}_{\mathcal{B}}^* - t B^{-1} \mathbf{a}^{(E)} = \mathbf{x}_{\mathcal{B}}^* - t \mathbf{d}, \quad (**)$$

where  $\mathbf{d}$  is found by solving  $B \mathbf{d} = \mathbf{a}^{(E)}$ . Let  $t^*$  denote the smallest  $t \geq 0$  for which  $\mathbf{x}_{\mathcal{B}}(t)$  has a zero entry. Each zero entry in  $\mathbf{x}_{\mathcal{B}}(t^*)$  identifies a column in the current basis that may leave. Pick one; use  $L$  as a symbol for the leaving index. Then the leaving column is  $\mathbf{a}^{(L)}$ . (If  $\mathbf{x}_{\mathcal{B}}(t)$  never develops a zero entry, sending  $t \rightarrow \infty$  proves problem is unbounded. Report that fact and stop.)

**Update.** Indices  $E$  and  $L$  are column numbers. At the beginning,  $E \in \mathcal{N}$  and  $L \in \mathcal{B}$ . Swap these two. Then go back to original problem and make the new block matrices  $B = A_{\mathcal{B}}$ ,  $N = A_{\mathcal{N}}$ , and cost vectors  $\mathbf{c}_{\mathcal{B}}^T$ ,  $\mathbf{c}_{\mathcal{N}}^T$ . Update the BFS  $\mathbf{x}^*$  by noting  $\mathbf{x}_{\mathcal{N}}^* = \mathbf{0}$ ;  $m - 1$  entries for  $\mathbf{x}_{\mathcal{B}}(t^*)$  appear in (\*\*); and  $x_E = t^*$ . Loop back to “Select Entering Col”.

**Example.** Here are some RSM pivots using Bland's rule for the problem

$$\begin{aligned} &\text{maximize } f = 3x_1 + 2x_2 + 4x_3 \\ &\text{subject to } \quad x_1 + x_2 + 2x_3 + x_4 = 4 \\ &\quad \quad \quad 2x_1 + 3x_3 + x_5 = 5 \\ &\quad \quad \quad 2x_1 + x_2 + 3x_3 + x_6 = 7 \\ &\quad \quad \quad x_j \geq 0 \end{aligned}$$

**Solution.** Setup:

$$A = \begin{bmatrix} 1 & 1 & 2 & 1 & 0 & 0 \\ 2 & 0 & 3 & 0 & 1 & 0 \\ 2 & 1 & 3 & 0 & 0 & 1 \end{bmatrix}, \quad \mathbf{b} = \begin{bmatrix} 4 \\ 5 \\ 7 \end{bmatrix},$$

$$\mathbf{c}^T = [3 \quad 2 \quad 4 \quad 0 \quad 0 \quad 0].$$

An easy BFS comes from choosing  $\mathcal{B} = \{4, 5, 6\}$ , so  $\mathcal{N} = \{1, 2, 3\}$ , giving

$$B = \begin{pmatrix} x_4 & x_5 & x_6 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}, \quad N = \begin{pmatrix} x_1 & x_2 & x_3 \\ 1 & 1 & 2 \\ 2 & 0 & 3 \\ 2 & 1 & 3 \end{pmatrix},$$

$$\mathbf{c}_B^T = \begin{pmatrix} x_4 & x_5 & x_6 \\ 0 & 0 & 0 \end{pmatrix}, \quad \mathbf{c}_N^T = \begin{pmatrix} x_1 & x_2 & x_3 \\ 3 & 2 & 4 \end{pmatrix},$$

$$\mathbf{x}_B^* = B^{-1}\mathbf{b} = \begin{pmatrix} x_4 \\ x_5 \\ x_6 \end{pmatrix} = \begin{pmatrix} 4 \\ 5 \\ 7 \end{pmatrix}, \quad f^* = 0.$$

*First iteration:*

- (1) Select entering variable using objective coeffs  $\mathbf{c}_N^T - \mathbf{c}_B^T B^{-1}N$ .

- (a) Solve for  $\mathbf{y}$  in

$$\mathbf{y}^T = \mathbf{c}_B^T B^{-1}, \quad \text{i.e., } \mathbf{y}^T B = \mathbf{c}_B^T.$$

Easy:  $\mathbf{y}^T = \mathbf{c}_B^T = [0 \quad 0 \quad 0]$ .

- (b) Write and scan vector

$$\mathbf{z}_N^T = \mathbf{y}^T N - \mathbf{c}_N^T = -\mathbf{c}_N^T = \begin{pmatrix} x_1 & x_2 & x_3 \\ -3 & -2 & -4 \end{pmatrix}.$$

Select  $x_1$  to enter (Bland's Rule). So  $E = 1$ ,  $\mathbf{a}^{(E)} = \mathbf{a}^{(1)}$ ,  $x_E = x_1$ .

- (2) Select leaving variable, noting  $Nx_N = t\mathbf{a}^{(\text{in})} = t\mathbf{a}^{(1)}$  so  $\mathbf{x}_B(t) = \mathbf{x}_B(0) - td$ .

- (a) Solve for  $\mathbf{d}$  in

$$\mathbf{d} = B^{-1}\mathbf{a}^{(1)}, \quad \text{i.e., } B\mathbf{d} = \mathbf{a}^{(1)}.$$

Easy:  $\mathbf{d} = \mathbf{a}^{(1)}$ .

(b) Monitor

$$\mathbf{x}_{\mathcal{B}}(t) = \begin{matrix} x_4 \\ x_5 \\ x_6 \end{matrix} \begin{pmatrix} 4 \\ 5 \\ 7 \end{pmatrix} - t \begin{pmatrix} 1 \\ 2 \\ 2 \end{pmatrix} = \begin{matrix} x_4 \\ x_5 \\ x_6 \end{matrix} \begin{pmatrix} 4-t \\ 5-2t \\ 7-2t \end{pmatrix}.$$

As  $t$  increases,  $t^* = 5/2$  is the smallest value where  $\mathbf{x}_{\mathcal{B}}(t)$  picks up a zero component. (Smallest choice makes sure  $\mathbf{x}_{\mathcal{B}}(t^*)$  stays feasible.) Variable  $x_5$  labels that slot, so it will leave. Write  $L = 5$ , so  $\mathbf{x}_L = x_5$ ,  $\mathbf{a}^{(L)} = \mathbf{a}^{(5)}$ .

(3) Update everything.

(a) New BFS refers to sets  $\mathcal{B}$  and  $\mathcal{N}$  above:

$$\mathbf{x}^*(t^*) = \begin{bmatrix} x_{\mathcal{B}}(t^*) \\ x_{\mathcal{N}}(t^*) \end{bmatrix} = \begin{matrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ x_6 \end{matrix} \begin{pmatrix} 5/2 \\ 0 \\ 0 \\ 3/2 \\ 0 \\ 2 \end{pmatrix}.$$

(b) New basis selection sets  $\mathcal{B} = \{1, 4, 6\}$  and  $\mathcal{N} = \{2, 3, 5\}$ .

(c) New partitioned matrices

$$B = \begin{matrix} & x_1 & x_4 & x_6 \\ \begin{pmatrix} 1 & 1 & 0 \\ 2 & 0 & 0 \\ 2 & 0 & 1 \end{pmatrix}, & & & \end{matrix} \quad N = \begin{matrix} & x_2 & x_3 & x_5 \\ \begin{pmatrix} 1 & 2 & 0 \\ 0 & 3 & 1 \\ 1 & 3 & 0 \end{pmatrix}, & & & \end{matrix}$$

$$\mathbf{c}_{\mathcal{B}}^T = \begin{matrix} & x_1 & x_4 & x_6 \\ \begin{pmatrix} 3 & 0 & 0 \end{pmatrix}, & & & \end{matrix} \quad \mathbf{c}_{\mathcal{N}}^T = \begin{matrix} & x_2 & x_3 & x_5 \\ \begin{pmatrix} 2 & 4 & 0 \end{pmatrix}, & & & \end{matrix}$$

$$\mathbf{x}_{\mathcal{B}}^* = B^{-1}\mathbf{b} = \begin{matrix} x_1 \\ x_4 \\ x_6 \end{matrix} \begin{pmatrix} 5/2 \\ 3/2 \\ 2 \end{pmatrix}, \quad f^* = 15/2.$$

*Second iteration:*

(1) Select entering variable.

(a) Solve for  $y$  in

$$\mathbf{y}^T = \mathbf{c}_{\mathcal{B}}^T B^{-1}, \quad \text{i.e.,} \quad \mathbf{y}^T B = \mathbf{c}_{\mathcal{B}}^T,$$

$$\text{i.e.,} \quad [y_1 \quad y_2 \quad y_3] \begin{matrix} & x_1 & x_4 & x_6 \\ \begin{pmatrix} 1 & 1 & 0 \\ 2 & 0 & 0 \\ 2 & 0 & 1 \end{pmatrix} \end{matrix} = \begin{matrix} & x_1 & x_4 & x_6 \\ \begin{pmatrix} 3 & 0 & 0 \end{pmatrix}. \end{matrix}$$

Get  $y_1 = 0$ ,  $y_3 = 0$ ,  $y_2 = 3/2$ :  $\mathbf{y}^T = [0 \quad 3/2 \quad 0]$ .

(b) Write and scan vector

$$\begin{aligned} \mathbf{z}_{\mathcal{N}}^T &= \mathbf{y}^T N - \mathbf{c}_{\mathcal{N}}^T = [0 \quad 3/2 \quad 0] \begin{pmatrix} x_2 & x_3 & x_5 \\ 1 & 2 & 0 \\ 0 & 3 & 1 \\ 1 & 3 & 0 \end{pmatrix} - \begin{pmatrix} x_2 & x_3 & x_5 \\ 2 & 4 & 0 \end{pmatrix} \\ &= \begin{pmatrix} x_2 & x_3 & x_5 \\ -2 & 1/2 & 3/2 \end{pmatrix}. \end{aligned}$$

Select  $x_2$  to enter (Bland's Rule). Thus  $E = 2$ ,  $\mathbf{a}^{(E)} = \mathbf{a}^{(2)}$ ,  $x_E = x_2$ .

(2) Select Leaving Variable, noting  $\mathbf{x}_{\mathcal{B}}(t) = \mathbf{x}_{\mathcal{B}}(0) - td$ .

(a) Solve for  $\mathbf{d}$  in

$$\mathbf{d} = B^{-1}\mathbf{a}^{(in)}, \quad \text{i.e.,} \quad B\mathbf{d} = \mathbf{a}^{(2)}$$

$$\text{i.e.,} \quad \begin{pmatrix} x_1 & x_4 & x_6 \\ 1 & 1 & 0 \\ 2 & 0 & 0 \\ 2 & 0 & 1 \end{pmatrix} \begin{bmatrix} d_1 \\ d_2 \\ d_3 \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix}.$$

Middle row gives  $d_1 = 0$ , then  $d_2 = 1$  and  $d_3 = 1$ . So  $\mathbf{d} = (0, 1, 1)$ .

(b) Monitor

$$\mathbf{x}_{\mathcal{B}}(t) = \begin{pmatrix} x_1 \\ x_4 \\ x_6 \end{pmatrix} \begin{pmatrix} 5/2 \\ 3/2 \\ 2 \end{pmatrix} - t \begin{pmatrix} 0 \\ 1 \\ 1 \end{pmatrix} = \begin{pmatrix} x_1 \\ x_4 \\ x_6 \end{pmatrix} \begin{pmatrix} 5/2 \\ 3/2 - t \\ 2 - t \end{pmatrix}$$

As  $t$  increases,  $t^* = 3/2$  is the smallest value where  $\mathbf{x}_{\mathcal{B}}(t)$  picks up a zero component. Variable  $x_4$  labels that slot, so it will leave. Write  $L = 4$ ,  $x_L = x_4$ ,  $\mathbf{a}^{(L)} = \mathbf{a}^{(4)}$ .

(3) Update everything.

(a) New BFS refers to sets  $\mathcal{B}$  and  $\mathcal{N}$  above:

$$\mathbf{x}^*(t^*) = \begin{bmatrix} \mathbf{x}_{\mathcal{B}}(t^*) \\ \mathbf{x}_{\mathcal{N}}(t^*) \end{bmatrix} = \begin{pmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ x_6 \end{pmatrix} \begin{pmatrix} 5/2 \\ 3/2 \\ 0 \\ 0 \\ 0 \\ 1/2 \end{pmatrix}$$

(b) New basis selection sets  $\mathcal{B} = \{1, 2, 6\}$  and  $\mathcal{N} = \{3, 4, 5\}$ .

(c) New partitioned matrices

$$B = \begin{matrix} & x_1 & x_2 & x_6 \\ \begin{pmatrix} 1 & 1 & 0 \\ 2 & 0 & 0 \\ 2 & 1 & 1 \end{pmatrix}, & & & \end{matrix} \quad N = \begin{matrix} & x_3 & x_4 & x_5 \\ \begin{pmatrix} 2 & 1 & 0 \\ 3 & 0 & 1 \\ 3 & 0 & 0 \end{pmatrix}, & & & \end{matrix}$$

$$\mathbf{c}_B^T = \begin{matrix} & x_1 & x_2 & x_6 \\ \begin{pmatrix} 3 & 2 & 0 \end{pmatrix}, & & & \end{matrix} \quad \mathbf{c}_N^T = \begin{matrix} & x_3 & x_4 & x_5 \\ \begin{pmatrix} 4 & 0 & 0 \end{pmatrix}, & & & \end{matrix}$$

$$\mathbf{x}_B^* = B^{-1}\mathbf{b} = \begin{matrix} x_1 \\ x_2 \\ x_6 \end{matrix} \begin{pmatrix} 5/2 \\ 3/2 \\ 1/2 \end{pmatrix}, \quad f^* = 25/2.$$

*Third iteration:*

(1) Select entering variable.

(a) Solve for  $\mathbf{y}$  in

$$\mathbf{y}^T = \mathbf{c}_B^T B^{-1}, \quad \text{i.e.,} \quad \mathbf{y}^T B = \mathbf{c}_B^T,$$

$$\text{i.e.,} \quad [y_1 \quad y_2 \quad y_3] \begin{matrix} & x_1 & x_2 & x_6 \\ \begin{pmatrix} 1 & 1 & 0 \\ 2 & 0 & 0 \\ 2 & 1 & 1 \end{pmatrix} = \begin{pmatrix} x_1 & x_2 & x_6 \\ 3 & 2 & 0 \end{pmatrix}.$$

Get  $y_3 = 0$ , then  $y_1 = 2$ , then  $y_2 = 1/2$ :  $\mathbf{y}^T = [2 \quad 1/2 \quad 0]$ .

(b) Write and scan vector

$$\mathbf{z}_N^T = \mathbf{y}^T N - \mathbf{c}_N^T = [2 \quad 1/2 \quad 0] \begin{matrix} & x_3 & x_4 & x_5 \\ \begin{pmatrix} 2 & 1 & 0 \\ 3 & 0 & 1 \\ 3 & 0 & 0 \end{pmatrix} - \begin{pmatrix} x_3 & x_4 & x_5 \\ 4 & 0 & 0 \end{pmatrix}$$

$$= \begin{matrix} & x_3 & x_4 & x_5 \\ \begin{pmatrix} 3/2 & 2 & 1/2 \end{pmatrix}.$$

All components are positive, so the current BFS is the **UNIQUE MAXIMIZER!** To report, recall the full solution vector  $\mathbf{x}^*(t^*)$  shown explicitly in part 3(a) of the Second Iteration above. ////