

Linear Programming Standard Equality Form and Solution Properties

Yinyu Ye

Stanford University and CUHK SZ (Sabbatical Leave)

Currently Visiting CUHK and HK PolyU

<https://web.stanford.edu/class/msande211x/handout.shtml>

Chapters 2.3-2.5, 4.1-4.2, 4.5

LP in Standard (**Equality**) Form

$$\min \quad c^T x = \sum_{j=1}^n c_j x_j$$

$$\text{s.t.} \quad a_1 x = \sum_{j=1}^n a_{1j} x_j = b_1$$

$$a_2 x = \sum_{j=1}^n a_{2j} x_j = b_2$$

...

$$a_m x = \sum_{j=1}^n a_{mj} x_j = b_m$$

$$x \geq 0$$



$$\begin{aligned} & \min \quad c^T x \\ \text{s.t.} \quad & Ax = b, \\ & x \geq 0 \end{aligned}$$

Reduction to Standard Form

- max $\mathbf{c}^T \mathbf{x}$ to min $-\mathbf{c}^T \mathbf{x}$
- Eliminating "free" variables: substitute with the difference of two nonnegative variables

$$x := x^l - x^{ll}, \quad (x^l, x^{ll}) \geq 0.$$

- Eliminating inequalities: add a slack variable

$$\mathbf{a}^T \mathbf{x} \leq b \Rightarrow \mathbf{a}^T \mathbf{x} + s = b, \quad s \geq 0$$

$$\mathbf{a}^T \mathbf{x} \geq b \Rightarrow \mathbf{a}^T \mathbf{x} - s = b, \quad s \geq 0$$

Reduction of the Production Problem

$$\begin{aligned} \max \quad & x_1 + 2x_2 \\ \text{s.t.} \quad & x_1 \leq 1 \\ & x_2 \leq 1 \\ & x_1 + x_2 \leq 1.5 \\ & x_1 \geq 0 \\ & x_2 \geq 0 \end{aligned}$$



$$\begin{aligned} \min \quad & -x_1 - 2x_2 \\ \text{s.t.} \quad & x_1 + x_2 + x_3 = 1 \\ & x_1 + x_2 + x_4 = 1 \\ & x_1 + x_2 + x_5 = 1.5 \\ & (x_1, x_2, x_3, x_4, x_5) \geq 0 \end{aligned}$$

x_3, x_4 , and x_5 are called **slack variables**

We know how to identify corners/extreme-points of the LP feasible region defined all by linear inequalities. What about corners in this LP standard equality form?

How to Identify Corners in LP Equality Form

Basic and Basic Feasible Solution

In the LP standard form, select m linearly independent columns, denoted by the variable index set B , from A . Solve

$$A \mathbf{x} = \mathbf{b} \quad \Leftrightarrow \quad A_B \mathbf{x}_B = \mathbf{b}, \mathbf{x}_N = \mathbf{0}$$

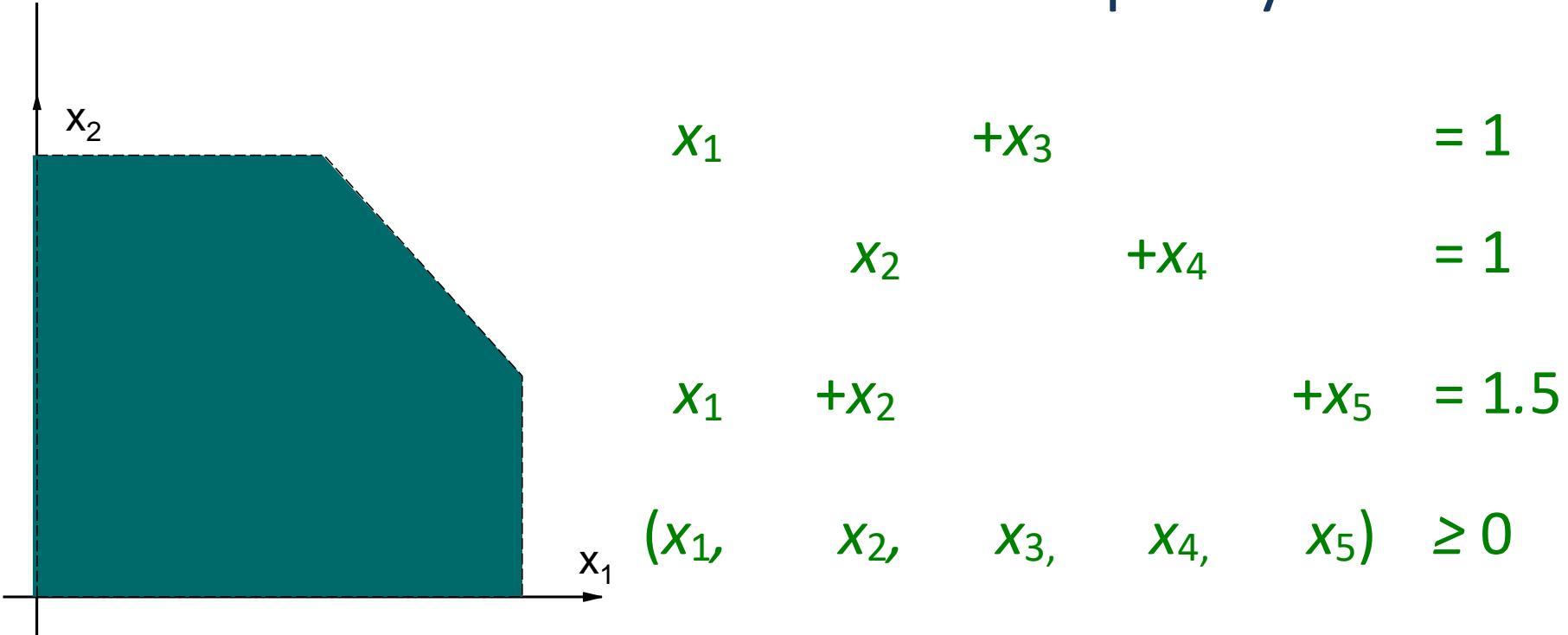
for the dimension- m vector \mathbf{x}_B . By setting the variables, \mathbf{x}_N , of \mathbf{x} corresponding to the remaining columns of A equal to zero, we obtain a solution \mathbf{x} such that $A\mathbf{x} = \mathbf{b}$.

Then, \mathbf{x} is said to be a **basic solution** to (LP) with respect to the **basic variable set** B . The variables in \mathbf{x}_B are called **basic variables**, those in \mathbf{x}_N are **nonbasic variables**, and A_B is called a **basis**.

If a basic solution $\mathbf{x}_B \geq \mathbf{0}$, then \mathbf{x} is called a **basic feasible solution**, or **BFS**. Note that A_B and \mathbf{x}_B follow the same index order in B .

Two BFS are **adjacent** if they differ by exactly one basic variable.

BS of the Production Problem in Equality Form



Basis	3,4,5	1,4,5	3,4,1	3,2,5	3,4,2	1,2,3	1,2,4	1,2,5
Feasible?	✓	✓		✓		✓	✓	
x_1, x_2	0, 0	1, 0	1.5, 0	0, 1	0, 1.5	.5, 1	1, .5	1, 1

BFS and Corner Point Equivalence Theorem

Theorem Consider the feasible region in the standard LP form. Then, a basic feasible solution and a corner (extreme) point are equivalent; the former is algebraic and the latter is geometric. Moreover, Two corners are neighboring if exact one variable difference in basis

- Feasible directions of an BFS: an **increasing** direction of the nonbasic variables (they equal 0 right now).
- Extreme feasible direction: the increasing direction of a nonbasic variable x_j : $x_B = (A_B)^{-1}\mathbf{b} - (A_B)^{-1}\mathbf{a}_j x_j$
- Optimality test: No improving (extreme) **feasible** direction exists

Feasible Directions at a BFS and Optimality Test

- Recall at a BFS: $\mathbf{A}_B \mathbf{x}_B + \mathbf{A}_N \mathbf{x}_N = \mathbf{b}$, and $\mathbf{x}_B \geq \mathbf{0}$ and $\mathbf{x}_N = \mathbf{0}$.

Thus we can express \mathbf{x}_B in terms of \mathbf{x}_N ,

$$\mathbf{x}_B = (\mathbf{A}_B)^{-1} \mathbf{b} - (\mathbf{A}_B)^{-1} \mathbf{A}_N \mathbf{x}_N. \quad \text{Reduced Objective}$$

Then, $\mathbf{c}^T \mathbf{x} = \mathbf{c}^T_B \mathbf{x}_B + \mathbf{c}^T_N \mathbf{x}_N = (\mathbf{c}^T_N - \mathbf{c}^T_B (\mathbf{A}_B)^{-1} \mathbf{A}_N) \mathbf{x}_N + \mathbf{c}^T_B (\mathbf{A}_B)^{-1} \mathbf{b}$

- Note that increase any one variable of \mathbf{x}_N is an **extreme feasible direction**. Thus, for the BFS to be optimal, any (extreme) feasible direction must be an **ascent direction**, or

$$(\mathbf{c}^T_N - \mathbf{c}^T_B (\mathbf{A}_B)^{-1} \mathbf{A}_N) \geq \mathbf{0}$$

is necessary and sufficient for the current BFS being optimal!

- This vector is called the **reduced cost coefficient vector** or **reduced gradient vector** from the current BFS. Note that reduced cost coefficients for basic variables are all zeros.

The Simplex Method: Shadow-Price and Reduced Cost Vectors

We first introduce and compute an intermediate shadow-price/multiplier vector:

$$\mathbf{y}^T = \mathbf{c}_B^T (\mathbf{A}_B)^{-1}, \text{ or } \mathbf{y}^T \mathbf{A}_B = \mathbf{c}_B^T,$$

by solving a system of linear equations.

Then we compute reduced cost $\mathbf{r}^T = \mathbf{c}^T - \mathbf{y}^T \mathbf{A}$, where \mathbf{r}_N is the reduced cost vector for nonbasic variables (and $\mathbf{r}_B = \mathbf{0}$ always).

If one of \mathbf{r}_N is negative, then an improving (extreme) feasible direction is find by increasing the corresponding nonbasic variable value.

In the LP production example, suppose the basic variable set $B = \{3, 4, 5\}$.

$$\begin{array}{lllll}
 \text{min} & -x_1 & -2x_2 & & \\
 \text{s.t.} & x_1 & +x_3 & = 1 \\
 & & x_2 & +x_4 & = 1 \\
 & x_1 & +x_2 & +x_5 & = 1.5 \\
 & x_1, x_2, x_3, x_4, x_5 & \geq 0.
 \end{array}$$

$$c_N = \begin{pmatrix} -1 \\ -2 \end{pmatrix}, c_B = \begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}, A_B = I, A_N = \begin{pmatrix} 1 & 0 \\ 0 & 1 \\ 1 & 1 \end{pmatrix},$$

$$A_B^{-1} = I, y^T = (0 \ 0 \ 0), \ r_N^T = (-1 \ -2).$$

Thus, increasing either x_1 and x_2 is a **feasible** and **improving** direction and the variable is called the incoming basic variable...

In the LP production example, suppose the basic variable set $B = \{1, 2, 3\}$.

$$\begin{array}{llllll}
 \text{min} & -x_1 & -2x_2 & & & \\
 \text{s.t.} & x_1 & & +x_3 & & = 1 \\
 & & x_2 & & +x_4 & = 1 \\
 & x_1 & +x_2 & & +x_5 & = 1.5 \\
 & x_1, & x_2, & x_3, & x_4, & x_5 & \geq 0.
 \end{array}$$

$$\boxed{
 \begin{aligned}
 c_N &= \begin{pmatrix} 0 \\ 0 \end{pmatrix}, c_B = \begin{pmatrix} -1 \\ -2 \\ 0 \end{pmatrix}, A_B = \begin{pmatrix} 1 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 1 & 0 \end{pmatrix}, A_N = \begin{pmatrix} 0 & 0 \\ 1 & 0 \\ 0 & 1 \end{pmatrix}, \\
 A_B^{-1} &= \begin{pmatrix} 0 & -1 & 1 \\ 0 & 1 & 0 \\ 1 & 1 & -1 \end{pmatrix}, \quad y^T = (0 \ -1 \ -1), \quad r_N^T = (1 \ 1).
 \end{aligned}
 }$$

Thus, this BFS is **optimal**

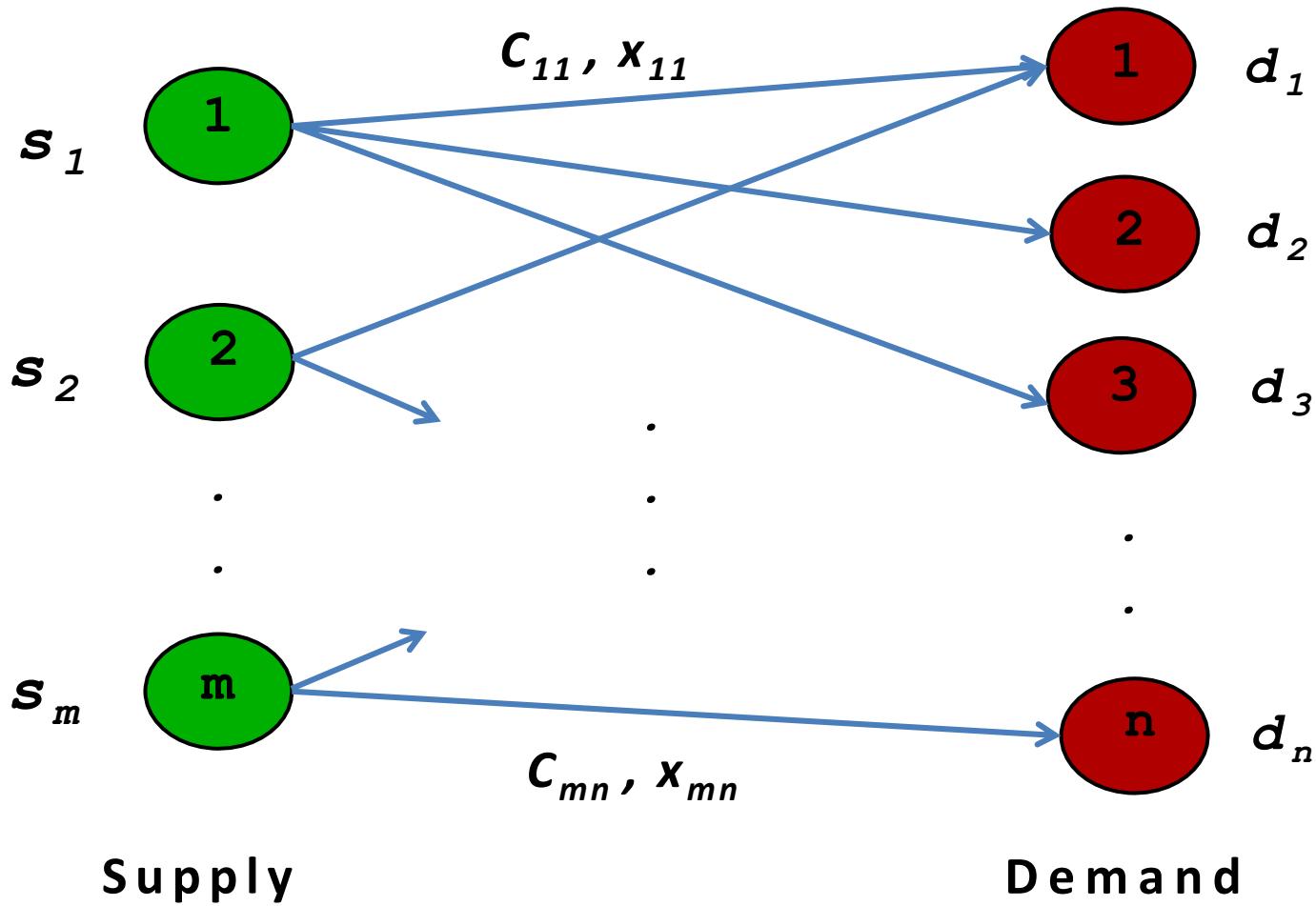
The Transportation Simplex Method

$$\begin{aligned} \min \quad & \sum_{i=1}^m \sum_{j=1}^n c_{ij} x_{ij} \\ \text{s.t.} \quad & \sum_{j=1}^n x_{ij} = s_i, \quad \forall i = 1, \dots, m \\ & \sum_{i=1}^m x_{ij} = d_j, \quad \forall j = 1, \dots, n \\ & x_{ij} \geq 0, \quad \forall i, j \end{aligned}$$

Assume that the total supply equal the total demand. Thus, exactly one equality constraint is redundant.

At each step the simplex method attempts to send units along a route that is **unused (non-basic)** in the current BFS, while eliminating one of the routes that is currently being used **(basic)**.

Transportation and Supply Chain Network



The Transportation Data Table

	1	2	3	4	Supply
1	12	13	4	6	500
2	6	4	10	11	700
3	10	9	12	4	800
Demand	400	900	200	500	2000

Transportation Simplex Method: Phase I

1. Start with the cell in the **northwest corner cell**
2. Allocate as many units as possible, consistent with the **available** supply and demand.
3. Move one cell to **right** if there is remaining supply; otherwise, move one cell **down**.
4. goto Step 2.

				500
				700
				800
400	900	200	500	

North-West Corner Method: Compute a BFS

400				100
				700
				800
0	900	200	500	

North-West Corner Method: Compute a BFS

400	100			0
				700
				800
0	800	200	500	

North-West Corner Method: Compute a BFS

400	100			0
	700			0
				800
0	100	200	500	

North-West Corner Method: Compute a BFS

400	100			0
	700			0
	100			700
0	0	200	500	

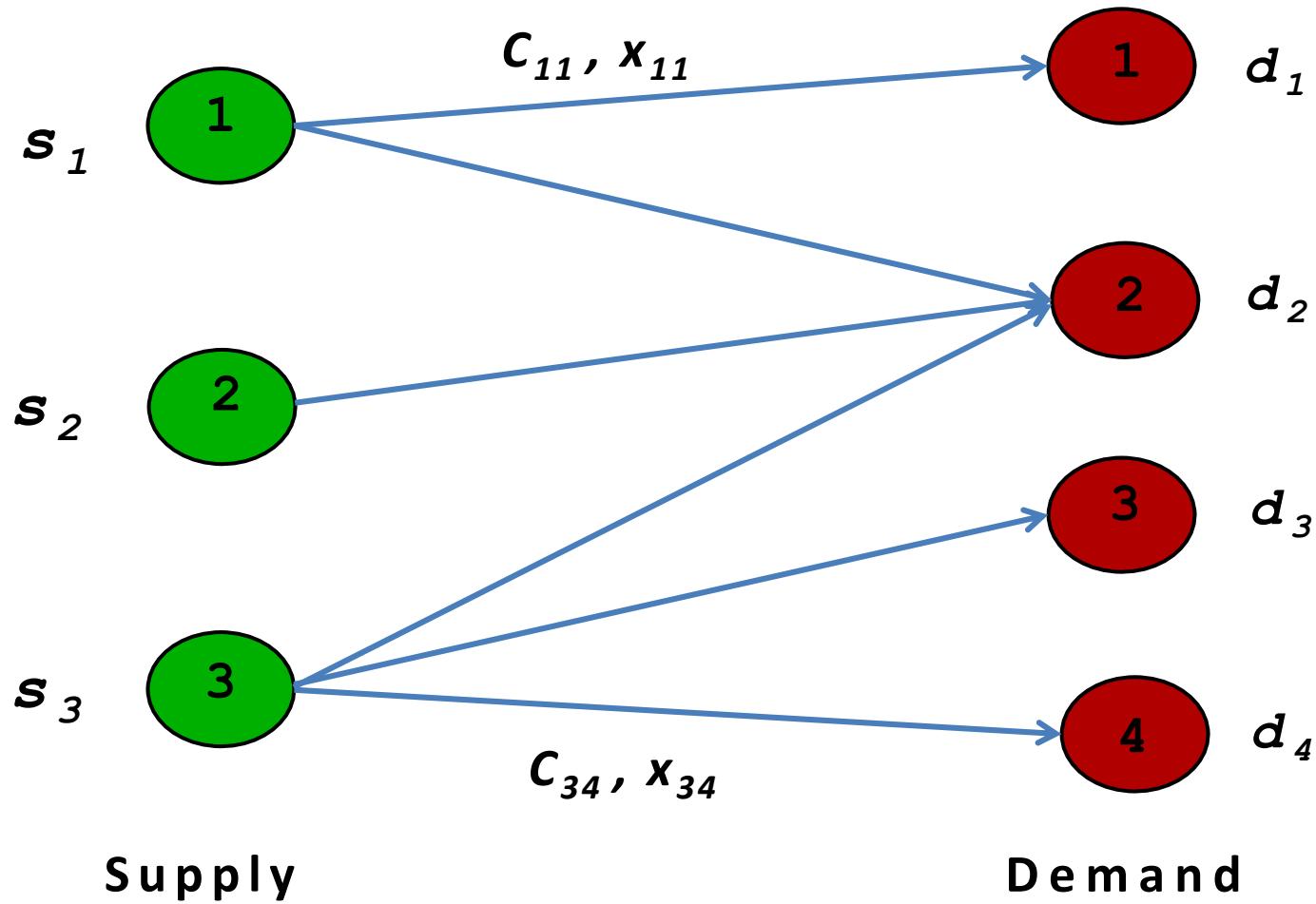
North-West Corner Method: Compute a BFS

400	100			0
	700			0
	100	200		500
0	0	0	500	

North-West Corner Method: Compute a BFS

400	100			0
	700			0
	100	200	500	0
0	0	0	0	

A BFS as a “Tree” Structure in the Network



(Tailored) Transportation Simplex Method: Phase II

1. Determine the **shadow prices** (for each supply side u_i and each demand side v_j) from every **USED** cell (**basic variable**)

$$\mathbf{y}^T = \mathbf{c}^T_B (A_B)^{-1} \Rightarrow \mathbf{y}^T A_B = \mathbf{c}^T_B \Rightarrow u_i + v_j = c_{ij}$$

One can always set $v_n = 0$ by viewing the last demand constraint redundant. Then do back-substitution...

Step 1: Compute Shadow Prices

400 12	100 13			0 $u_1 =$
	700 4			0 $u_2 =$
	100 9	200 12	500 4	0 $u_3 =$
0 $v_1 =$	0 $v_2 =$	0 $v_3 =$	0 $v_4 = 0$	

Step 1: Compute Shadow Prices

400 12	100 13			0 $u_1 =$
	700 4			0 $u_2 =$
	100 9	200 12	500 4	0 $u_3 = 4$
0 $v_1 =$	0 $v_2 =$	0 $v_3 =$	0 $v_4 = 0$	

Step 1: Compute Shadow Prices

400 12	100 13			0 $u_1 =$
	700 4			0 $u_2 =$
	100 9	200 12	500 4	0 $u_3 = 4$
0 $v_1 =$	0 $v_2 =$	0 $v_3 = 8$	0 $v_4 = 0$	

Step 1: Compute Shadow Prices

400 12	100 13			0 $u_1 =$
	700 4			0 $u_2 =$
	100 9	200 12	500 4	0 $u_3 = 4$
0 $v_1 =$	0 $v_2 = 5$	0 $v_3 = 8$	0 $v_4 = 0$	

Step 1: Compute Shadow Prices

400 12	100 13			0 $u_1 =$
	700 4			0 $u_2 = -1$
	100 9	200 12	500 4	0 $u_3 = 4$
0 $v_1 =$	0 $v_2 = 5$	0 $v_3 = 8$	0 $v_4 = 0$	

Step 1: Compute Shadow Prices

400 12	100 13			0 $u_1=8$
	700 4			0 $u_2=-1$
	100 9	200 12	500 4	0 $u_3=4$
0 $v_1=$	0 $v_2=5$	0 $v_3=8$	0 $v_4=0$	

Step 1: Compute Shadow Prices

400 12	100 13			0 $u_1=8$
	700 4			0 $u_2=-1$
	100 9	200 12	500 4	0 $u_3=4$
0 $v_1=4$	0 $v_2=5$	0 $v_3=8$	0 $v_4=0$	

Transportation Simplex Method: Phase II

1. Determine the **shadow prices** (for each supply side u_i and each demand side v_j) from every **USED** cell (**basic variable**)

$$\mathbf{y}^T = \mathbf{c}^T_B (A_B)^{-1} \Rightarrow \mathbf{y}^T A_B = \mathbf{c}^T_B \Rightarrow u_i + v_j = c_{ij}$$

One can always set $v_n = 0$ by viewing the last demand constraint redundant; then do back-substitution...

2. Calculate the **reduced costs** for the **UNUSED** cells (non-basic variable)

$$r_N = \mathbf{c}^T_N - \mathbf{y}^T A_N \Rightarrow r_{ij} = c_{ij} - u_i - v_j$$

If the reduced cost for every unused cell is nonnegative, then STOP: declare **OPTIMAL**

Step 2: Compute Reduced Costs

400 12	100 13	4	6	500 $u_1=8$
6	700 4	10	11	700 $u_2=-1$
10	100 9	200 12	500 4	800 $u_3=4$
400 $v_1=4$	900 $v_2=5$	200 $v_3=8$	500 $v_4=0$	2000

$$r_{ij} = c_{ij} - u_i - v_j$$

Step 2: Compute Reduced Costs

400 12 0	100 13 0	4 -12	6 -2	500 $u_1=8$
6 3	700 4 0	10 3	11 12	700 $u_2=-1$
10 2	100 9 0	200 12 0	500 4 0	800 $u_3=4$
400 $v_1=4$	900 $v_2=5$	200 $v_3=8$	500 $v_4=0$	2000

Reduced costs are computed in RED

Transportation Simplex Method: Phase II

1. Determine the **shadow prices** (for each supply side u_i and each demand side v_j) from every **USED** cell (**basic variable**)

$$\mathbf{y}^T = \mathbf{c}^T_B (A_B)^{-1} \Rightarrow \mathbf{y}^T A_B = \mathbf{c}^T_B \Rightarrow u_i + v_j = c_{ij}$$

One can always set $v_n = 0$ by viewing the last demand constraint redundant; then do back-substitution...

2. Calculate the **reduced costs** for the **UNUSED** cells (non-basic variable)

$$r_N = \mathbf{c}^T_N - \mathbf{y}^T A_N \Rightarrow r_{ij} = c_{ij} - u_i - v_j$$

If the reduced cost for every unused cell is nonnegative, then STOP:
declare **OPTIMAL**

3. Select an unused cell with the **most negative** reduced cost as **in-coming**. Using a **chain-reaction-cycle**, determine the **max** units (α) that can be allocated to the in-coming cell and adjust the allocation appropriately. Update the values of the **new set of USED (basic) cells** (a new BFS).