

## LP Homework 5

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### 3.19

While solving a standard form problem, we arrive at the following tableau, with  $x_3, x_4$  and  $x_5$  being the basic variables:

$-10$	$\delta$	$-2$	$0$	$0$	$0$
$4$	$-1$	$\eta$	$1$	$0$	$0$
$1$	$\alpha$	$-4$	$0$	$1$	$0$
$\beta$	$\gamma$	$3$	$0$	$0$	$1$

The entries  $\alpha, \beta, \gamma, \delta, \eta$  in the tableau are unknown parameters. For each one of the following statements, find some parameter values that will make the statement true.

- (a) The current solution is optimal and there are multiple optimal solutions.
- (b) The optimal cost is  $-\infty$ .
- (c) The current solution is feasible but not optimal.

Solution.

(a) Since the current solution is optimal, yet the reduced cost  $\bar{c}_2$  is negative, the current solution must be degenerate, indicating  $\beta = 0$ . In the next iteration, we will choose the  $x_2$  to enter the basis and  $x_5$  to exit. Let  $\beta + \frac{2}{3}\gamma \geq 0$  and then the next tableau will be optimal. For the optimal solutions to be multiple, we may set  $\delta = 0$  and  $\alpha > 0$ . Then we can make  $x_4$  an exiting variable and  $x_1$  an entering variable without changing the

optimal cost since  $\delta = 0$ . The following tableau could be a possible choice:

-10	0	-2	0	0	0
4	-1	0	1	0	0
1	1	-4	0	1	0
0	0	3	0	0	1

The next tableau will be:

-10	0	0	0	0	2/3
4	-1	0	1	0	0
1	1	0	0	1	4/3
0	0	1	0	0	1/3

Adding  $x_1$  to the basis and removing  $x_4$  from the basis, we get the following tableau:

-10	0	0	0	0	2/3
5	0	0	1	0	4/3
1	1	0	0	1	4/3
0	0	1	0	0	1/3

Both  $\mathbf{x} = (0, 0, 4, 1, 0)^T$  and  $\mathbf{x} = (1, 0, 5, 0, 0)^T$  are optimal.

(b) For feasibility, we must demand  $\beta \geq 0$ . Since the problem is unbounded if no components of an exiting column are positive; by setting  $\delta < 0$  and  $\alpha, \gamma \leq 0$ , we can make  $x_1$  an exiting variable and the optimal cost  $-\infty$ . The following tableau could be a possible choice:

-10	-3	-2	0	0	0
4	-1	-1	1	0	0
1	-1	-4	0	1	0
1	-1	3	0	0	1

(c) For feasibility, we must demand  $\beta \geq 0$ . Since the current solution is not optimal, we may set  $\beta > 0$  and then move in the direction of  $x_2$  to get a lower cost. The following tableau could be a possible choice:

-10	0	-2	0	0	0
4	-1	0	1	0	0
1	0	-4	0	1	0
3	0	3	0	0	1

In the next iteration, we will choose the  $x_2$  to enter the basis and  $x_5$  to exit. The next tableau will be:

$$\begin{array}{c|ccccc} -8 & 0 & 0 & 0 & 0 & 2/3 \\ \hline 4 & -1 & 0 & 1 & 0 & 0 \\ 5 & 0 & 0 & 0 & 1 & 4/3 \\ 1 & 0 & 1 & 0 & 0 & 1/3 \end{array}$$

which is the optimal situation.

### 3.22

Consider the following linear programming problem with a single constraint:

$$\begin{array}{ll} \text{maximize} & \sum_{i=1}^n c_i x_i \\ \text{subject to} & \sum_{i=1}^n a_i x_i = b \\ & x_i \geq 0, \quad i = 1, \dots, n. \end{array}$$

- Derive a simple test for checking the feasibility of this problem.
- Assuming that the optimal cost is finite, develop a simple method for obtaining an optimal solution directly.

Solution.

(a)

- If  $b = 0$ , then the problem is feasible because  $\mathbf{x} = \mathbf{0}$  is feasible.
- If  $b > 0$ , then we assert that the problem is feasible if and only if there exists  $a_j > 0$  for some  $j \in [1, n]$ .

Proof.

$\Rightarrow$  If the problem is feasible, then there exists  $\mathbf{x} \geq 0$  such that  $\sum_{i=1}^n a_i x_i = b$ .

If  $a_j \leq 0$  for all  $j \in [1, n]$ , then  $\sum_{i=1}^n a_i x_i \leq 0 < b$ , which is a contradiction.

$\Leftarrow$  If there exists  $a_j > 0$  for some  $j \in [1, n]$ , then we can set  $x_j = b/a_j$  and  $x_i = 0$  for all  $i \neq j$ . Then  $\mathbf{x}$  is feasible.

- If  $b < 0$ , then we assert that the problem is feasible if and only if there exists  $a_j < 0$  for some  $j \in [1, n]$ .

The proof is similar to the case  $b > 0$ .

(b)

Since the optimal cost is finite and the constraint set is a standard form polyhedron, there exists an optimal solution that is a basic feasible solution. By  $m = 1$ , we know that every BFS has at most one nonzero component.

1. If  $b = 0$ , then we assert that the optimal cost is 0.

Proof.

Let  $\mathbf{x} = \mathbf{0}$ , we obtain a cost of 0. If the optimal cost is not 0, then there exists a BFS  $\mathbf{x}^*$  such that  $\sum_{i=1}^n c_i x_i^* < 0$ . Since  $\mathbf{x}^*$  has at most one nonzero component, it then has exactly one nonzero component, say  $x_k^* > 0$  for some  $k \in [1, n]$ . Then we have  $a_k = 0$  and  $c_k < 0$ . Consider  $\mathbf{x} = \alpha \mathbf{e}_k$ ,  $\alpha > 0$ , where  $\mathbf{e}_k$  is the  $k$ th unit vector and feasibility satisfies. For  $\alpha$  sufficiently large, the optimal cost  $\sum_{i=1}^n c_i x_i = \alpha c_k$  is unbounded from below, which is a contradiction.

2. If  $b > 0$ , then every BFS has exactly one nonzero component. Let  $k := \arg \min_{i=1, \dots, n} \{ \frac{c_i b}{a_i} \mid a_i > 0 \}$ , then an optimal solution is  $\mathbf{x} = (0, \dots, 0, b/a_k, 0, \dots, 0)$ .

3. If  $b < 0$ , then every BFS has exactly one nonzero component. Let  $k := \arg \min_{i=1, \dots, n} \{ \frac{c_i b}{a_i} \mid a_i < 0 \}$ , then an optimal solution is  $\mathbf{x} = (0, \dots, 0, b/a_k, 0, \dots, 0)$ .

### 3.26

(The big-M method) Consider the variant of the big- $M$  method in which  $M$  is treated as an undetermined large parameter. Prove the following.

(a) If the simplex method terminates with a solution  $(\mathbf{x}, \mathbf{y})$  for which  $\mathbf{y} = \mathbf{0}$ , then  $\mathbf{x}$  is an optimal solution to the original problem.

(b) If the simplex method terminates with a solution  $(\mathbf{x}, \mathbf{y})$  for which  $\mathbf{y} \neq \mathbf{0}$ , then the original problem is infeasible.

(c) If the simplex method terminates with an indication that the optimal cost in the auxiliary problem is  $-\infty$ , show that the original problem is either infeasible or its optimal cost is  $-\infty$ . *Hint:* When the simplex method terminates, it has discovered a feasible direction  $\mathbf{d} = (\mathbf{d}_x, \mathbf{d}_y)$  of cost decrease. Show that  $\mathbf{d}_y = \mathbf{0}$ .

(d) Provide examples to show that both alternatives in part (c) are possible.

Proof.

The original problem can be written as:

$$\begin{aligned} & \text{minimize} \quad \mathbf{c}^T \mathbf{x} \\ & \text{subject to} \quad \mathbf{Ax} = \mathbf{b} \\ & \quad \mathbf{x} \geq \mathbf{0}. \end{aligned}$$

The auxiliary problem can be written as:

$$\begin{aligned} & \text{minimize} \quad \mathbf{c}^T \mathbf{x} + M \sum_{i=1}^n y_i \\ & \text{subject to} \quad \mathbf{Ax} + \mathbf{y} = \mathbf{b} \\ & \quad \mathbf{x} \geq \mathbf{0}. \\ & \quad \mathbf{y} \geq \mathbf{0}. \end{aligned}$$

(a) Assume that there exists a feasible primal solution  $\mathbf{z}$  such that  $\mathbf{c}^T \mathbf{z} < \mathbf{c}^T \mathbf{x}$ . It is obvious that  $(\mathbf{z}, \mathbf{0})$  is also feasible for the auxiliary problem. Then we have  $\mathbf{c}^T \mathbf{z} + M \cdot 0 < \mathbf{c}^T \mathbf{x} + M \cdot 0$ , which is a contradiction to the fact that  $(\mathbf{x}, \mathbf{0})$  is optimal to the auxiliary problem.

(b) Assume that the big- $M$  method terminates with a solution  $(\mathbf{x}, \mathbf{y})$  with  $\mathbf{y} \neq \mathbf{0}$ , whereas the original problem has a feasible point  $\mathbf{z}$ . It is obvious that  $(\mathbf{z}, \mathbf{0})$  is also feasible for the auxiliary problem. Then we have  $\mathbf{c}^T \mathbf{z} + M \cdot 0 < \mathbf{c}^T \mathbf{x} + M \cdot \sum_{i=1}^n y_i$  for  $M$  sufficiently large and  $\mathbf{y} \neq \mathbf{0}$ , which is a contradiction to the fact that  $(\mathbf{x}, \mathbf{y})$  is optimal to the auxiliary problem.

(c) Assume that the original problem has an optimal solution  $\mathbf{z} \in \mathbb{R}^n$ . When the big- $M$  method terminates with an indication that the optimal cost is  $-\infty$ , it has discovered a feasible direction  $\mathbf{d} = (\mathbf{d}_x, \mathbf{d}_y)$  of cost decrease

$$\mathbf{c}^T \mathbf{d}_x + M \sum_{i=1}^n d_{yi} < 0$$

such that  $(\mathbf{x}, \mathbf{y}) + \theta(\mathbf{d}_x, \mathbf{d}_y)$  can be feasible for the auxiliary problem for any  $\theta > 0$ , which indicates that  $\mathbf{d} \geq \mathbf{0}$  with at least one nonzero component.

We assert that  $\mathbf{d}_y$  must be  $\mathbf{0}$ , otherwise we could take  $M$  large enough to make  $\mathbf{c}^T \mathbf{d}_x + M \sum_{i=1}^n d_{yi} > 0$ . Then we immediately have  $\mathbf{c}^T \mathbf{d}_x < 0$ .

Notice that  $\mathbf{d}_x$  is a feasible direction of cost decrease for the original problem,

because  $\mathbf{A}(\mathbf{x} + \mathbf{d}_x) + (\mathbf{y} + \mathbf{d}_y) = \mathbf{b} \Rightarrow \mathbf{A}\mathbf{d}_x = \mathbf{b} - (\mathbf{A}\mathbf{x} + \mathbf{y}) = \mathbf{0}$ . Then we have  $\mathbf{c}^T \mathbf{d}_x < 0$ , which is a contradiction to the fact that  $\mathbf{z}$  is an optimal solution.

(d) First consider an infeasible original problem:

$$\begin{aligned} \text{minimize} \quad & x_1 - 2x_2 \\ \text{subject to} \quad & -x_1 - x_3 = 1 \\ & -x_1 + x_3 = 1. \\ & \mathbf{x} \geq 0. \end{aligned}$$

Its big- $M$  problem:

$$\begin{aligned} \text{minimize} \quad & x_1 - 2x_2 + M(y_1 + y_2) \\ \text{subject to} \quad & -x_1 - x_3 + y_1 = 1 \\ & -x_1 + x_3 + y_2 = 1. \\ & \mathbf{x} \geq 0. \\ & \mathbf{y} \geq 0. \end{aligned}$$

The initial tableau of the big- $M$  problem is:

$-2M$	$1 + 2M$	$-2$	$0$	$0$	$0$
$1$	$-1$	$0$	$-1$	$1$	$0$
$1$	$-1$	$0$	$1$	$0$	$1$

The second column is cost-reducing while none of its components is positive; thus, the big- $M$  problem is unbounded.

Then consider an unbounded original problem:

$$\begin{aligned} \text{minimize} \quad & -x_1 - x_2 \\ \text{subject to} \quad & x_1 - x_2 = 1 \\ & x_1, x_2 \geq 0. \end{aligned}$$

Its big- $M$  problem:

$$\begin{aligned} \text{minimize} \quad & -x_1 - x_2 + My_1 \\ \text{subject to} \quad & x_1 - x_2 + y_1 = 1 \\ & x_1, x_2, y_1 \geq 0. \end{aligned}$$

The initial tableau of the big- $M$  problem is:

$$\begin{array}{c|cccc} -M & -1-M & -1+M & 0 \\ \hline 1 & 1 & -1 & 1 \end{array}$$

Let  $y_1$  exit the basis and  $x_1$  enter the basis, we have:

$$\begin{array}{c|cccc} 1 & 0 & -2 & 1+M \\ \hline 1 & 1 & -1 & 1 \end{array}$$

The second column is cost-reducing while none of its components is positive; thus, the big- $M$  problem is unbounded.

### 3.28

Consider a linear programming problem in standard form with a bounded feasible set. Furthermore, suppose that we know the value of a scalar  $U$  such that any feasible solution satisfies  $x_i \leq U$ , for all  $i$ . Show that the problem can be transformed into an equivalent one that contains the constraint  $\sum_{i=1}^n x_i = 1$ .  
Proof.

The original problem can be written as:

$$\begin{array}{ll} \text{minimize} & \mathbf{c}^T \mathbf{x} \\ \text{subject to} & \mathbf{Ax} = \mathbf{b} \\ & \mathbf{x} \geq 0 \end{array}$$

Notice that from  $x_i \leq U$  for all  $i$  we have  $\frac{1}{nU} \sum_{i=1}^n x_i \leq 1$ . Introduce the new variable  $x_{n+1}$  and the constraint turns into an equation  $\sum_{i=1}^n \frac{1}{nU} x_i + x_{n+1} = 1$ . We now show that the following problem with  $n+1$  variables is equivalent

to the original problem:

$$\begin{aligned}
& \text{minimize} && \tilde{\mathbf{c}}^T \tilde{\mathbf{x}} \\
& \text{subject to} && \tilde{\mathbf{A}} \tilde{\mathbf{x}} = \tilde{\mathbf{b}} \\
& && \tilde{\mathbf{x}} \geq 0 \\
& && \sum_{i=1}^{n+1} \tilde{x}_i = 1.
\end{aligned}$$

where  $\tilde{\mathbf{c}} = [nU \cdot \mathbf{c}, 0]^T$ ,  $\tilde{\mathbf{A}} = [\mathbf{A}, \mathbf{0}]$ ,  $\tilde{\mathbf{b}} = \frac{1}{nU} \mathbf{b}$ .

1. If  $\mathbf{x}$  is optimal to the original problem, then  $\tilde{\mathbf{x}} = [\frac{1}{nU} \mathbf{x}, 1 - \frac{1}{nU} \sum_{i=1}^n x_i]^T$  is optimal to the new problem.

It is easy to verify that  $\tilde{\mathbf{x}}$  is feasible for the new problem. Suppose that there exists another feasible solution  $\tilde{\mathbf{x}} = [\tilde{\mathbf{x}}_1, \tilde{x}_{n+1}]^T$ ,  $\tilde{\mathbf{x}}_1 \in \mathbb{R}^n$  such that  $\tilde{\mathbf{c}}^T \tilde{\mathbf{x}}' < \tilde{\mathbf{c}}^T \tilde{\mathbf{x}}$ . Then let  $\mathbf{x}' = nU \cdot \tilde{\mathbf{x}}_1$  which is feasible to the original problem, we have  $\mathbf{c}^T \mathbf{x}' = \tilde{\mathbf{c}}^T \tilde{\mathbf{x}}' < \tilde{\mathbf{c}}^T \tilde{\mathbf{x}} = \mathbf{c}^T \mathbf{x}$ , which contradicts the optimality of  $\mathbf{x}$ .

2. If  $\tilde{\mathbf{x}} = [\tilde{\mathbf{x}}_1, \tilde{x}_{n+1}]^T$ ,  $\tilde{\mathbf{x}}_1 \in \mathbb{R}^n$  is optimal to the new problem, then  $\mathbf{x} = nU \cdot \tilde{\mathbf{x}}_1$  is optimal to the original problem. Suppose that there exists another feasible solution  $\mathbf{x}'$  to the original problem such that  $\mathbf{c}^T \mathbf{x}' < \mathbf{c}^T \mathbf{x}$ . Then let  $\tilde{\mathbf{x}}' = [\frac{1}{nU} \mathbf{x}', 1 - \frac{1}{nU} \sum_{i=1}^n x'_i]^T$  which is feasible to the new problem, we have  $\tilde{\mathbf{c}}^T \tilde{\mathbf{x}}' = \mathbf{c}^T \mathbf{x}' < \mathbf{c}^T \mathbf{x} = \tilde{\mathbf{c}}^T \tilde{\mathbf{x}}$ , which contradicts the optimality of  $\tilde{\mathbf{x}}$ .

Hence, the two problems are equivalent.