

Introduction to Optimization Theory

Homework Assignment 2

Chen Zhiyang, 2017011377

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Ex. 3.3

Proof

\Rightarrow :

If \mathbf{d} is a feasible direction at \mathbf{x} , there exists a scalar $\lambda > 0$, s.t. $\mathbf{x} + \lambda\mathbf{d} \in P$.
Therefore,

$$\mathbf{A}(\mathbf{x} + \lambda\mathbf{d}) = \mathbf{Ax} + \lambda\mathbf{Ad} = \mathbf{0} \Rightarrow \mathbf{Ad} = \mathbf{0},$$

and

$$\mathbf{x} + \lambda\mathbf{d} \geq \mathbf{0} \Rightarrow \text{for each } i \text{ s.t. } x_i = 0, x_i + \lambda d_i \geq 0 \Rightarrow d_i \geq 0.$$

\Leftarrow :

Let

$$\lambda = \min_{x_i \neq 0} -\frac{d_i}{x_i},$$

obviously we have $\mathbf{x} + \lambda\mathbf{d} \geq \mathbf{0}$, and $\mathbf{Ad} = \mathbf{0} \Rightarrow \mathbf{Ax} + \lambda\mathbf{Ad} = \mathbf{A}(\mathbf{x} + \lambda\mathbf{d}) = \mathbf{0}$, which means \mathbf{d} is a feasible direction.

Ex. 3.4

Proof

If \mathbf{d} is a feasible direction, there exists a scalar $\lambda > 0$ s.t. $\mathbf{x}^* + \lambda\mathbf{d} \in P$. We have

(1) $\mathbf{A}(\mathbf{x} + \lambda\mathbf{d}) = \mathbf{0} \Rightarrow \mathbf{Ax} + \lambda\mathbf{Ad} = \mathbf{0} \Rightarrow \mathbf{Ad} = \mathbf{0}.$

(2) $\mathbf{Dx}^* = \mathbf{f}, \mathbf{D}(\mathbf{x}^* + \lambda\mathbf{d}) \leq \mathbf{f} \Rightarrow \lambda\mathbf{Dd} < \mathbf{0} \Rightarrow \mathbf{Dd} < \mathbf{0}.$

If $\mathbf{A}\mathbf{d} = \mathbf{0}$, $\mathbf{D}\mathbf{d} \leq \mathbf{0}$, let

$$\lambda = \min_{(\mathbf{E}\mathbf{d})_i > 0} \frac{(\mathbf{g} - \mathbf{E}\mathbf{x}^*)_i}{(\mathbf{E}\mathbf{d})_i}.$$

Note that $\lambda > 0$ in that $\mathbf{E}\mathbf{x}^* < \mathbf{g}$ (if the set $\{i : (\mathbf{E}\mathbf{d})_i > 0\}$ is empty, let λ be any positive number).

We have

$$(1) \quad \mathbf{A}(\mathbf{x}^* + \lambda\mathbf{d}) = \mathbf{A}\mathbf{x}^* + \lambda\mathbf{A}\mathbf{d} = \mathbf{0}.$$

$$(2) \quad \mathbf{D}(\mathbf{x}^* + \lambda\mathbf{d}) = \mathbf{D}\mathbf{x}^* + \lambda\mathbf{D}\mathbf{d} \leq \mathbf{f}.$$

$$(3) \quad \mathbf{E}(\mathbf{x}^* + \lambda\mathbf{d}) \leq \mathbf{g}.$$

Therefore, \mathbf{d} is a feasible direction iff $\mathbf{A}\mathbf{d} = \mathbf{0}$, $\mathbf{D}\mathbf{d} \leq \mathbf{0}$.

Ex. 3.5

Let a direction $\mathbf{d} = (d_1, d_2, d_3)^T$. \mathbf{d} is feasible at \mathbf{x} if there exists some $\lambda > 0$ s.t. $\mathbf{x} + \lambda\mathbf{d} \in P$. To require this, we have to make $\lambda(d_1 + d_2 + d_3) + 1 = 1$, which means $d_3 = -d_1 - d_2$. Also, $(\lambda d_1, \lambda d_2, 1 + \lambda(-d_1 - d_2)) \geq \mathbf{0} \Rightarrow d_1, d_2 \geq 0$.

Therefore, the set of feasible directions at \mathbf{x} is $\{(d_1, d_2, -d_1 - d_2) : d_1, d_2 \geq 0\}$.

Ex. 3.6

(a)

Proof

Suppose \mathbf{y} is an arbitrary feasible solution other than \mathbf{x} , let $\mathbf{d} = \mathbf{y} - \mathbf{x}$, then $\mathbf{A}\mathbf{d} = \mathbf{A}\mathbf{y} - \mathbf{A}\mathbf{x} = \mathbf{0}$. Let N be the set of nonbasic indices associated with \mathbf{B} . Rewrite this as

$$\mathbf{B}\mathbf{d}_B + \sum_{i \in N} \mathbf{A}_i d_i = \mathbf{0}.$$

Since \mathbf{B} is invertible, we have $\mathbf{d}_B = -\sum_{i \in N} \mathbf{B}^{-1} \mathbf{A}_i d_i$. Therefore,

$$\mathbf{c}^T \mathbf{d} = \mathbf{c}_B^T \mathbf{d}_B + \sum_{i \in N} c_i d_i = \sum_{i \in N} (c_i - \mathbf{c}_B^T \mathbf{B}^{-1} \mathbf{A}_i) d_i = \sum_{i \in N} \bar{c}_i d_i.$$

If for all $i \in N$, $y_i = 0$, we have $\mathbf{A}\mathbf{y} = \mathbf{B}\mathbf{y}_B = \mathbf{b}$, which means $\mathbf{x} = \mathbf{y}$. Therefore, there exists $j \in N$ s.t. $y_j > 0$, and

$$\mathbf{c}^T \mathbf{d} = \sum_{i \in N} \bar{c}_i d_i = \sum_{i \in N} \bar{c}_i y_i \geq \bar{c}_j y_j > 0.$$

(b)

Proof

Suppose $\bar{c}_j \leq 0, j \in N$. Let \mathbf{d} be the j -th basic direction. As \mathbf{x} is non-degenerate, we know \mathbf{d} is always a feasible direction. There exists $\lambda > 0$, s.t. $\mathbf{x} + \lambda \mathbf{d} \in P$. Then $\mathbf{c}^T \mathbf{d} = \bar{c}_j d_j = \bar{c}_j \leq 0$. By choosing sufficiently small $\lambda > 0$ so that $\mathbf{x} + \lambda \mathbf{d} \in P$, we get $\lambda \mathbf{c}^T \mathbf{d} \leq 0$, which means the cost of $\mathbf{x} + \lambda \mathbf{d}$ is not larger than the cost of \mathbf{x} . However, we know \mathbf{x} is the unique optimal solution, which leads to a contradiction.

Ex. 3.7

Proof

That the new LP problem has an optimal cost of zero means for all \mathbf{d} , s.t. $\mathbf{A}\mathbf{d} = \mathbf{0}, d_i \geq 0, i \in Z$, we have $\mathbf{c}^T \mathbf{d} \geq 0$. This is equivalent to at \mathbf{x} , for any feasible direction \mathbf{d} , $\mathbf{c}^T \mathbf{d} \geq 0$, which means \mathbf{x} is optimal.

Ex. 3.12

(a)

We add two artificial variables y_1, y_2 . The constraints become:

$$x_1 - x_2 + y_1 = 2,$$

$$x_1 + x_2 + y_2 = 6,$$

$$x_1, x_2, y_1, y_2 \geq 0.$$

It's easy to see $(x_1, x_2, y_1, y_2) = (0, 0, 2, 6)$ is a basic feasible solution.

(b)

In this problem we have

$$\mathbf{A} = \begin{bmatrix} 1 & -1 & 1 & 0 \\ 1 & 1 & 0 & 1 \end{bmatrix}, \mathbf{b} = \begin{bmatrix} 2 \\ 6 \end{bmatrix}, \mathbf{c} = \begin{bmatrix} -2 \\ -1 \\ 0 \\ 0 \end{bmatrix}.$$

The initial basic variables are y_1 and y_2 , so at first $\mathbf{B} = \mathbf{I}_2$.

Now we get the initial tableau.

0	-2	-1	0	0
2	1	-1	1	0
6	1	1	0	1

Let x_1 enter the basis and y_1 exit the basis.

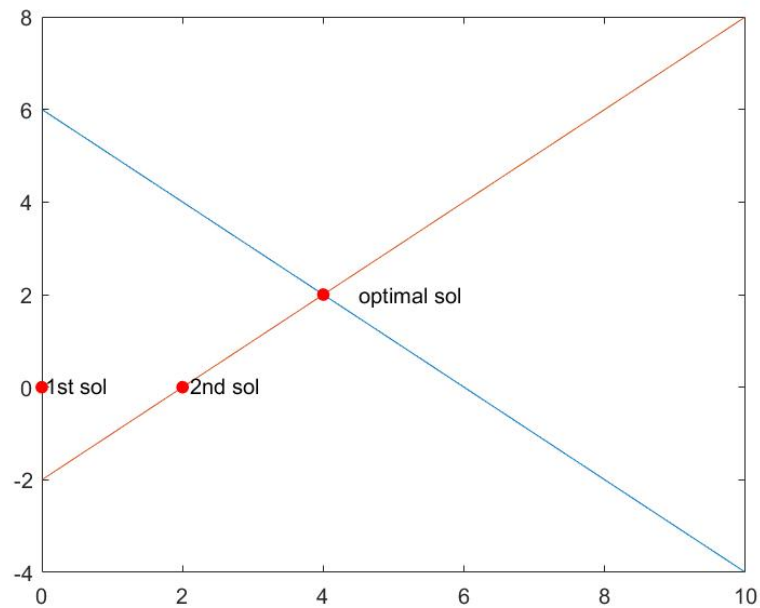
4	0	-3	2	0
2	1	-1	1	0
4	0	2	-1	1

Let x_2 enter the basis and y_2 exit the basis.

10	0	0	0.5	1.5
4	1	0	0.5	0.5
2	0	1	-0.5	0.5

Now all the components of $\bar{\mathbf{c}}$ is non-negative. We get the optimal solution $(x_1, x_2) = (4, 2)$, and the optimal cost is -10 .

(c)



Ex. 3.17

Phase I:

We transform the original LP problem into:

$$\begin{aligned} & \text{minimize } y_1 + y_2 + y_3, \\ & \text{subj. to } \begin{cases} x_1 + 3x_2 + 4x_4 + x_5 + y_1 = 2, \\ x_1 + 2x_2 - 3x_4 + x_5 + y_2 = 2, \\ -x_1 + 4x_2 + 3x_3 + y_3 = 1, \\ x_1, x_2, \dots, x_5, y_1, y_2, y_3 \geq 0. \end{cases} \end{aligned}$$

We begin with a BFS $\mathbf{x} = (0, 0, 0, 0, 0, 2, 2, 1)^T$.

-5	-1	-1	-3	-1	-2	0	0	0
2	1	3	0	4	1	1	0	0
2	1	2	0	-3	1	0	1	0
1	-1	-4	3	0	0	0	0	1

Let x_3 enter the basis and y_3 exit the basis.

-4	-2	-5	0	-1	-2	0	0	1
2	1	3	0	4	1	1	0	0
2	1	2	0	-3	1	0	1	0
$\frac{1}{3}$	$-\frac{1}{3}$	$-\frac{4}{3}$	1	0	0	0	0	$\frac{1}{3}$

Let x_1 enter the basis and y_1 exit the basis.

0	0	1	0	7	0	2	0	1
2	1	3	0	4	1	1	0	0
0	0	-1	0	-7	0	-1	1	0
1	0	$-\frac{1}{3}$	1	$-\frac{4}{3}$	$\frac{1}{3}$	$\frac{1}{3}$	0	$\frac{1}{3}$

Let x_2 enter the basis and y_2 exit the basis.

0	0	0	0	0	0	1	1	1
2	1	0	0	-17	1	-2	3	0
0	0	1	0	7	0	1	-1	0
1	0	0	1	$\frac{11}{3}$	$\frac{1}{3}$	$\frac{2}{3}$	$-\frac{1}{3}$	$\frac{1}{3}$

Now we get an initial BFS $\mathbf{x} = (2, 0, 1, 0, 0)^T$.

Phase II:

-7	0	0	0	3	-5
2	1	0	0	-17	1
0	0	1	0	7	0
1	0	0	1	$\frac{11}{3}$	$\frac{1}{3}$

Let x_5 enter the basis and x_1 exit the basis.

3	5	0	0	-82	0
2	1	0	0	-17	1
0	0	1	0	7	0
$\frac{1}{3}$	$-\frac{1}{3}$	0	1	$\frac{28}{3}$	0

Let x_4 enter the basis and x_2 exit the basis.

3	5	$\frac{82}{7}$	0	0	0
2	1	$\frac{17}{7}$	0	0	17
0	0	$\frac{1}{7}$	0	1	0
$\frac{1}{3}$	$-\frac{1}{3}$	$-\frac{4}{3}$	1	$\frac{28}{3}$	0

Now we get the optimal solution $\mathbf{x} = (0, 0, \frac{1}{3}, 0, 2)^T$, and the optimal cost is -3.

Ex. 3.18

(a)

False. In one iteration of the simplex method, we always choose some j s.t. $\bar{c}_j < 0$. If the solution does move a positive solution, the cost must decrease.

(b)

True. When we implement the full tableau method, we find some j s.t. $\bar{c}_j < 0$. Assume the k -th variable exits the basis. We know in the tableau the element in the pivot row and the pivot column must be positive. Therefore, we must add a positive multiple of the pivot row to the zero-th row. The element in the k -th column and the pivot row is 1, which means after the iteration, \bar{c}_k must be positive, so it cannot reenter in the next iteration.

(c)

False. Consider the example demonstrated in class:

		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

Let x_1 enter the basis and x_5 exit the basis. We get:

		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

In class, the example let x_4 exit the basis. However, we can notice that the ratio $x_{B(1)}/u_1$ and $x_{B(2)}/u_2$ are both 10. We can let x_1 exit the basis just after it entered the basis.

(d)

False. Consider the LP problem:

$$\text{minimize } x_1 + x_2 + x_3,$$

$$\text{subj. to } x_1 + x_2 + x_3 = 1, x_1, x_2, x_3 \geq 0.$$

$\mathbf{A}_1, \mathbf{A}_2, \mathbf{A}_3$ are all nondegenerate basis, but $\mathbf{x} = (1, 0, 0)^T, (0, 1, 0)^T$ or $(0, 0, 1)^T$ are all optimal solutions.

(e)

False. Consider the same example as **(d)**. $\mathbf{x} = (0.5, 0.5, 0)^T$ is an optimal solution while it has two positive components.