

Lesson 19. Degeneracy, Convergence, Multiple Optimal Solutions

0 Warm up

Example 1. Suppose we are using the simplex method to solve the following canonical form LP:

$$\vec{c} = (10, 3, 0, 0, 0)$$

	maximize	10x + 3y			
	subject to	x + y + s ₁	=	4	(1)
		5x + 2y + s ₂	=	11	(2)
		y + s ₃	=	4	(3)
		x	≥	0	(4)
		y	≥	0	(5)
		s ₁	≥	0	(6)
		s ₂	≥	0	(7)
		s ₃	≥	0	(8)

n = 5
m = 3
⇒ n - m = 2

Let $\mathbf{x} = (x, y, s_1, s_2, s_3)$. Our current BFS is $\mathbf{x}^t = (0, 4, 0, 3, 0)$ with basis $\mathcal{B}^t = \{y, s_1, s_2\}$. The simplex directions are $\mathbf{d}^x = (1, 0, -1, -5, 0)$ and $\mathbf{d}^{s_3} = (0, -1, 1, 2, 1)$. Compute \mathbf{x}^{t+1} and \mathcal{B}^{t+1} .

$$\bar{c}_x = \vec{c}^T \vec{d}^x$$

$$= 10$$

$$\bar{c}_{s_3} = \vec{c}^T \vec{d}^{s_3}$$

$$= -3$$

⇒ \vec{d}^x is improving, since $\bar{c}_x > 0$
and this is a maximizing LP

⇒ x is entering

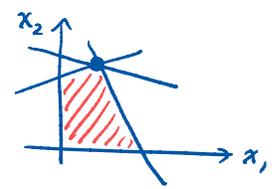
MRT: $\lambda_{\max} = \min \left\{ \frac{s_1}{-(-1)}, \frac{s_2}{-(-5)} \right\} = 0 \Rightarrow s_1 \text{ is leaving}$

⇒ $\vec{x}^{t+1} = \vec{x}^t + \lambda_{\max} \vec{d}^x$

$$= (0, 4, 0, 3, 0) + 0(1, 0, -1, -5, 0) = (0, 4, 0, 3, 0)$$

$\mathcal{B}^{t+1} = \{x, y, s_2\}$

- In the above example, the step size $\lambda_{\max} = 0$
- As a result, $\mathbf{x}^{t+1} = \mathbf{x}^t$: it looks like our solution didn't change!
- The basis did change, however: $\mathcal{B}^{t+1} \neq \mathcal{B}^t$
- Why did this happen?



1 Degeneracy

- A BFS x of an LP with n decision variables is **degenerate** if there are more than n constraints active at x
 - i.e. there are multiple collections of n linearly independent constraints that define the same x

Example 2. Is x^t in Example 1 degenerate? Why?

Yes. \bar{x}^t is active at $(1), (2), (3), (4), (6), (8)$
equality constraints nonnegativity constraints.

$$B^t = \{y, s_1, s_2\}$$

- In $x^t = (0, 4, 0, 3, 0)$ in Example 1, “too many” of the nonnegativity constraints are active
 - As a result, some of the basic variables are equal to zero
- Recall: a BFS of a canonical form LP with n decision variables and m equality constraints has

- m basic variables, potentially zero or nonzero
- $n - m$ nonbasic variables, always equal to 0

$$\begin{array}{l} Ax = b \quad] m \\ x \geq 0 \quad] n \end{array}$$

- Suppose x is a degenerate BFS, with $n + k$ active constraints ($k \geq 1$)
- Then $n + k - m$ nonnegativity bounds must be active, which is larger than $n - m$
- Therefore: a BFS x of a canonical form LP is degenerate if

at least one of the basic variables is equal to 0.

- As a result, a degenerate BFS may correspond to several bases

◦ e.g. in Example 1, the BFS $(0, 4, 0, 3, 0)$ has bases: $\{y, s_1, s_2\}, \{x, y, s_2\}$

- Every step of the simplex method
 - does not necessarily move to a geometrically adjacent extreme point
 - does move to an adjacent BFS (in particular, the bases differ by exactly 1 variable)
- At a degenerate BFS, the simplex method might “get stuck” for a few steps
 - Same BFS, different bases, different simplex directions
 - Zero-length moves: $\lambda_{\max} = 0$
- When $\lambda_{\max} = 0$, just proceed as usual
- Simplex computations will normally escape a sequence of zero-length moves and move away from the current BFS

2 Convergence

- In extreme cases, degeneracy can cause the simplex method to cycle over a set of bases that all represent the same extreme point
 - See Rader p. 291 for an example
- Can we guarantee that the simplex method terminates?
- Yes! Anticycling rules exist
- Easy anticycling rule: **Bland's rule**
 - Fix an ordering of the decision variables and rename them so that they have a common index
 - ◊ e.g. $(x, y, s_1, s_2, s_3) \rightarrow (x_1, x_2, x_3, x_4, x_5)$
 - Entering variable: choose nonbasic variable with smallest index among those corresponding to improving simplex directions
 - Leaving variable: choose basic variable with smallest index among those that define λ_{\max}

3 Multiple optimal solutions

- Suppose our current BFS is \mathbf{x}^t , and y is the entering variable
- The change in objective function value from \mathbf{x}^t to $\mathbf{x}^t + \lambda \mathbf{d}^y$ ($\lambda \geq 0$) is

$$\bar{c}^T(\bar{\mathbf{x}}^t + \lambda \bar{\mathbf{d}}^y) - \bar{c}^T \bar{\mathbf{x}}^t = \cancel{\bar{c}^T \bar{\mathbf{x}}^t} + \lambda \bar{c}^T \bar{\mathbf{d}}^y - \cancel{\bar{c}^T \bar{\mathbf{x}}^t} = \lambda \bar{c}^T \bar{\mathbf{d}}^y = \lambda \bar{c}_y$$

⇒ We can use reduced costs to compute changes in objective function

- Suppose we solve a canonical form maximization LP with decision variables $\mathbf{x} = (x_1, x_2, x_3, x_4, x_5)$ using the simplex method, and end up with:

$$\begin{aligned} \mathbf{x}^t &= (0, 150, 0, 200, 50) & \mathcal{B}^t &= \{x_2, x_4, x_5\} \\ \mathbf{d}^{x_1} &= \left(1, -\frac{1}{2}, 0, -\frac{3}{2}, -\frac{1}{2}\right) & \mathbf{d}^{x_3} &= \left(0, -\frac{1}{2}, 1, \frac{1}{2}, \frac{1}{2}\right) \\ \bar{c}_{x_1} &= 0 & \bar{c}_{x_3} &= -25 \end{aligned}$$

- Is \mathbf{x}^t optimal?

Yes, there are no improving simplex directions

- Are there multiple optimal solutions?

- Because the reduced cost $\bar{c}_{x_1} = 0$,

$\vec{\mathbf{d}}^{x_1}$ points towards other solutions w/ the same value as $\vec{\mathbf{x}}^t$

- Let's explore using x_1 as an entering variable:

$$\begin{aligned} \text{MRT: } \lambda_{\max} &= \min \left\{ \frac{150}{-(-\frac{1}{2})}, \frac{200}{-(-\frac{3}{2})}, \frac{50}{-(-\frac{1}{2})} \right\} = 100 & x_5 \text{ leaving} \\ \Rightarrow \vec{\mathbf{x}}^{t+1} &= \vec{\mathbf{x}}^t + \lambda_{\max} \vec{\mathbf{d}}^{x_1} = (0, 150, 0, 200, 50) + 100 \left(1, -\frac{1}{2}, 0, -\frac{3}{2}, -\frac{1}{2}\right) \\ &= (100, 100, 0, 50, 0) & \mathcal{B}^{t+1} &= \{x_1, x_2, x_4\} \\ \Rightarrow \vec{\mathbf{x}}^{t+1} &\text{ has the same value as } \vec{\mathbf{x}}^t \Rightarrow \vec{\mathbf{x}}^{t+1} \text{ is also optimal!} \end{aligned}$$

- In general, if there is a reduced cost equal to 0 at an optimal solution, there may be other optimal solutions
 - The zero reduced cost must correspond to a simplex direction with $\lambda_{\max} > 0$