Simplex algorithm (1/2)

15.093: Optimization

Dimitris Bertsimas Alexandre Jacquillat

MANAGEMENT SLOAN SCHOOL

Sloan School of Management Massachusetts Institute of Technology

Feasibility and optimality conditions

Background and motivation

$$(LO): \quad \min_{oldsymbol{x} \in \mathcal{P}} \quad oldsymbol{c}^{ op} oldsymbol{x}, \quad \text{where } \mathcal{P} = \{oldsymbol{x} \in \mathbb{R}^n_+ : oldsymbol{A} oldsymbol{x} = oldsymbol{b}\}$$

ullet Let us start from a basic feasible solution $x\in \mathcal{P}$

$$egin{aligned} m{A}m{x} &= m{b} \longrightarrow [m{B} \ m{N}]m{x} = m{b} \ m{x}_N &= m{0} \qquad m{x}_B = m{B}^{-1}m{b} \end{aligned}$$

• What if we moved away in direction $d \in \mathbb{R}^n$, by a small amount $\theta > 0$?

$$\boldsymbol{x} \leftarrow \boldsymbol{x} + \theta \boldsymbol{d}, \text{ with } \begin{cases} d_j = 1 & \text{ for non-basic variable } j \in \mathcal{N} \\ d_i = 0 & \text{ for other non-basic variables } i \neq j \in \mathcal{N} \\ \boldsymbol{d}_B = ?? & \text{ for basic variables in } \mathcal{B} \end{cases}$$

- 1. What does it take to retain feasibility: $x + \theta d \in \mathcal{P}$?
- 2. What does it take to improve the solution: $c^{\top}(x + \theta d) < c^{\top}x$?

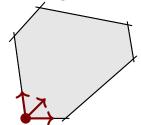
Feasibility conditions

Polyhedral constraints:

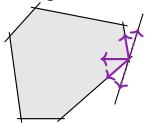
$$egin{aligned} m{A}(m{x}+m{ heta}m{d}) &= m{b} \implies m{A}m{d} = m{0} \ &\implies m{B}m{d}_B + m{A}_j = m{0} \ &\implies m{d}_B = -m{B}^{-1}m{A}_j \end{aligned}$$

- Non-negativity constraints:
 - If x is nondegenerate, $x_B > 0$ so $x_B + \theta d_B > 0$ if θ is small
 - If x is degenerate, $x + \theta d$ is not necessarily feasible if $\theta > 0$!

A non-degenerate BFS



A degenerate BFS



Optimality conditions

What does it take to improve the solution:

$$\begin{aligned} \boldsymbol{c}^{\top}(\boldsymbol{x} + \theta \boldsymbol{d}) < \boldsymbol{c}^{\top} \boldsymbol{x} & \Longrightarrow \boldsymbol{c}^{\top} \boldsymbol{d} < 0 \\ & \Longrightarrow \boldsymbol{c}_{B}^{\top} \boldsymbol{d}_{B} + c_{j} < 0 \\ & \Longrightarrow c_{j} - \boldsymbol{c}_{B}^{\top} \boldsymbol{B}^{-1} \boldsymbol{A}_{j} < 0 \end{aligned}$$

Definition

Reduced cost of variable x_i : $\bar{c}_i = c_i - c_R^{\top} B^{-1} A_i$

The reduced cost of basic variables is 0.

if
$$j \in B$$
, then $\overline{c}_j = c_j - \boldsymbol{c}_B^{\top} \boldsymbol{B}^{-1} \boldsymbol{A}_j = c_j - \boldsymbol{c}_B^{\top} \boldsymbol{e}_j = c_j - c_j = 0$

- The reduced cost of non-basic variables can be <0, 0 or >0
 - If there exists a non-basic variable $j \in N$ such that $\overline{c}_i < 0$, we might be able to improve the solution: $c^{\top}(x + \theta d) < c^{\top}x$
 - Otherwise, we have found an optimal solution

Characterization of optimal solutions

Theorem

Let x be a basic feasible solution associated with basis B and let \overline{c} be the vector of reduced costs. Then:

- 1. If $\overline{c} \geq 0$, then x is an optimal solution of (LO)
- 2. If x is an optimal solution of (LO) and is nondegenerate, then $\overline{c} \geq 0$
 - Proof of 1: proving optimality
 - ullet Consider a BFS x associated with basis B such that $\overline{c} \geq 0$
 - ullet Consider an arbitrary feasible solution $oldsymbol{y} \in \mathcal{P}$ and denote $oldsymbol{d} = oldsymbol{y} oldsymbol{x}$
 - Feasibility condition: Ax = b and Ay = b so Ad = 0, i.e.,

$$m{B}m{d}_B + \sum_{i \in \mathcal{N}} m{A}_i d_i = m{0}, \ \ ext{or} \ \ m{d}_B = -\sum_{i \in \mathcal{N}} m{B}^{-1} m{A}_i d_i$$

- ullet Feasibility condition: $oldsymbol{x}_N = oldsymbol{0}$ and $oldsymbol{y} \geq oldsymbol{0}$ so $oldsymbol{d}_N \geq oldsymbol{0}$
- Optimality check:

$$\boldsymbol{c}^{\top} \boldsymbol{y} - \boldsymbol{c}^{\top} \boldsymbol{x} = \boldsymbol{c}^{\top} \boldsymbol{d} = \boldsymbol{c}_{B}^{\top} \boldsymbol{d}_{B} + \sum_{i \in \mathcal{N}} c_{i} d_{i} = \sum_{i \in \mathcal{N}} \bar{c}_{i} d_{i} \geq 0$$

 $\rightarrow x$ is an optimal solution

Characterization of optimal solutions

Theorem

Let x be a basic feasible solution associated with basis B and let \overline{c} be the vector of reduced costs. Then:

- 1. If $\overline{c} \geq 0$, then x is an optimal solution of (LO)
- 2. If x is an optimal solution of (LO) and is nondegenerate, then $\overline{c} \geq 0$
 - Proof of 2: improving the cost
 - Assume by contradiction that $\bar{c}_j = c_j \boldsymbol{c}_B^{\top} \boldsymbol{B}^{-1} \boldsymbol{A}_j < 0$
 - Consider $\theta > 0$ and define $\boldsymbol{y} = \boldsymbol{x} + \theta \boldsymbol{d}$ with

$$\begin{cases} d_j = 1 \\ d_i = 0 \\ d_B = -\boldsymbol{B}^{-1}\boldsymbol{A}_j & \text{for other non-basic variables } i \neq j \in \mathcal{N} \end{cases}$$

- Cost reduction: $c^{\top}y c^{\top}x = \theta(c_j + c_B^{\top}d_B) = \theta \bar{c}_j < 0$
- Feasibility: ${m x} + \theta {m d}$ is feasible for $\theta > 0$ small enough
 - By construction, Ad = 0, so Ay = b
 - ullet Since $m{x}$ is nondegenerate, $m{x}_B > m{0}$ so $m{x}_B + heta m{d}_B > m{0}$ for $m{ heta}$ small enough
- $\rightarrow x$ is not an optimal solution

- ullet Consider a non-optimal basic feasible solution x
- Assume that you have found a non-basic variable j such that $\overline{c}_j < 0$

$$\boldsymbol{c}^{\top}(\boldsymbol{x} + \theta \boldsymbol{d}) = \boldsymbol{c}^{\top}\boldsymbol{x} + \theta \overline{c}_{j} < \boldsymbol{c}^{\top}\boldsymbol{x}$$

- In fact, the larger θ , the larger the cost reduction
- → Question: By how much can we improve the solution?
 - By construction, the new solution satisfies the polyhedral constraints:

$$A(x + \theta d) = \underbrace{Ax}_{=b} + \theta \underbrace{Ad}_{=0} = b$$

- What about non-negativity constraints: $x + \theta d \ge 0$?
 - If $d \geq 0$, then $x + \theta d \geq 0$ for all $\theta \geq 0$ and the problem is unbounded
 - If there exists j with $d_j < 0$, then $x + \theta d \ge 0$ requires $\theta \le -\frac{x_j}{d_j}$

$$\implies \text{ minimum ratio rule: } \qquad \theta^* = \min_{i=1,\cdots,m:d_{B(i)} < 0} \left(-\frac{x_{B(i)}}{d_{B(i)}} \right)$$

Example: constructing a basic feasible solution

- ullet $x \geq 0$ so it is a basic feasible solution
- Is there a better basic feasible solution?

(0,3,0)

Example: finding a direction of cost improvement

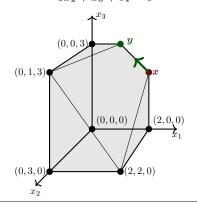
Example: moving to a new basic feasible solution

$$\min_{\substack{x,s \ge 0}} \quad x_1 + 5x_2 - 2x_3$$
s.t.
$$x_1 + x_2 + x_3 + s_1 = 4$$

$$x_1 + s_2 = 2$$

$$x_3 + s_3 = 3$$

$$3x_2 + x_3 + s_4 = 6$$



$$\boldsymbol{y} = (\mathbf{2} - \boldsymbol{\theta}, \mathbf{0}, \mathbf{2} + \boldsymbol{\theta}, \mathbf{0}, \boldsymbol{\theta}, \mathbf{1} - \boldsymbol{\theta}, \mathbf{4} - \boldsymbol{\theta})^{\top}$$

- We have found a direction that satisfies $oldsymbol{A} oldsymbol{y} = oldsymbol{b}$ and such that $oldsymbol{c}^ op oldsymbol{y} < oldsymbol{c}^ op oldsymbol{x}$
- How far can we go?

$$egin{aligned} 2- heta &\geq 0 \ 2+ heta &\geq 0 \ 1- heta &\geq 0 \ 4- heta &\geq 0 \end{aligned} \implies heta = 1 \ A = egin{bmatrix} 1 & 1 & 1 & 0 & 0 & 0 \ 1 & 0 & 0 & 1 & 0 & 0 \ 0 & 3 & 1 & 0 & 0 & 1 & 0 \ 0 & 0 & 1 & 0 & 0 & 0 & 1 \end{bmatrix}$$

- $\rightarrow x_6$ left the basis and x_5 entered the basis
- → Move from one extreme point to another

$$\min_{x,s>0} x_1 + 5x_2 - 2x_3$$

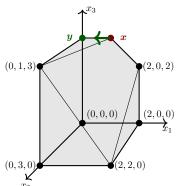
s.t.
$$x_1 + x_2 + x_3 + s_1 = 4$$

 $x_1 + s_2 = 2$

$$x_3 + s_3 = 3$$

$$x_3 + s_3 = 3$$

$$3x_2 + x_3 + s_4 = 6$$



$$m{B} = \left[egin{array}{cccc} 1 & 1 & 0 & 0 \ 1 & 0 & 1 & 0 \ 0 & 1 & 0 & 0 \ 0 & 1 & 0 & 1 \end{array}
ight] m{B}^{-1} = \left[egin{array}{cccc} 1 & 0 & -1 & 0 \ 0 & 0 & 1 & 0 \ -1 & 1 & 1 & 0 \ 0 & 0 & -1 & 1 \end{array}
ight]$$

$$\boldsymbol{x}_B = \boldsymbol{B}^{-1} \boldsymbol{b}$$

$$\boldsymbol{x} = (\mathbf{1}, \mathbf{0}, \mathbf{3}, \mathbf{0}, \mathbf{1}, \mathbf{0}, \mathbf{3})^{\top}$$

$$\overline{oldsymbol{c}}^{ op} = oldsymbol{c}^{ op} - oldsymbol{c}_B^{ op} oldsymbol{B}^{-1} oldsymbol{A} = (oldsymbol{0}, oldsymbol{13}, oldsymbol{0}, oldsymbol{-1}, oldsymbol{0}, oldsymbol{3}, oldsymbol{0})^{ op}$$

$$egin{aligned} egin{aligned} d_4 &= \mathbf{1} \ d_2 &= d_6 = \mathbf{0} \ d_B &= -B^{-1}A_4 = (\mathbf{-1}, \mathbf{0}, \mathbf{1}, \mathbf{0})^ op \ \end{pmatrix} \ &\Longrightarrow \ oldsymbol{y} &= (\mathbf{1} - oldsymbol{ heta}, \mathbf{0}, \mathbf{3}, oldsymbol{ heta}, \mathbf{1} + oldsymbol{ heta}, \mathbf{0}, \mathbf{3})^ op \end{aligned}$$

$$(2,0,0) \implies \boldsymbol{y} = (\mathbf{1} - \boldsymbol{\theta}, \mathbf{0}, \mathbf{3}, \boldsymbol{\theta}, \mathbf{1} + \boldsymbol{\theta}, \mathbf{0}, \mathbf{3})^{\top}$$

$$\implies y = (0, 0, 3, 1, 2, 0, 3)^{\top}$$

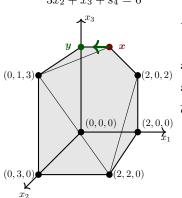
 $\rightarrow x_1$ left the basis and x_4 entered the basis

→ Move to yet another extreme point

Example: proving optimality

$$\begin{aligned} & \min_{x,s \geq 0} & x_1 + 5x_2 - 2x_3 \\ & \text{s.t.} & x_1 + x_2 + x_3 + s_1 = 4 \\ & x_1 + s_2 = 2 \\ & x_3 + s_3 = 3 \end{aligned}$$

$$3x_2 + x_3 + s_4 = 6$$



$$m{B} = \left[egin{array}{cccc} m{1} & m{1} & m{0} & m{0} \\ m{0} & m{0} & m{1} & m{0} \\ m{1} & m{0} & m{0} & m{0} \\ m{1} & m{0} & m{0} & m{1} \end{array}
ight] m{B}^{-1} = \left[egin{array}{cccc} m{0} & m{0} & m{1} & m{0} \\ m{0} & m{1} & m{0} & m{0} \\ m{0} & m{0} & -m{1} & m{1} \end{array}
ight]$$

$$\boldsymbol{x}_B = \boldsymbol{B}^{-1}\boldsymbol{b}$$

$$x = (0, 0, 3, 1, 2, 0, 3)^{\top}$$

$$oldsymbol{ar{c}}^ op = oldsymbol{c}^ op - oldsymbol{c}_B^ op oldsymbol{B}^{-1} oldsymbol{A} = (\mathbf{1}, \mathbf{11}, \mathbf{0}, \mathbf{0}, \mathbf{0}, \mathbf{2}, \mathbf{0})^ op$$

- → The reduced costs are all positive
- → Optimal solution: $x = (0, 0, 3, 1, 2, 0, 3)^{\top}$
- \rightarrow Optimal cost: -6

Simplex algorithm (1/2) The simplex algorithm

The simplex algorithm

One iteration

- Iterative moves from one extreme point to an adjacent one
- ightarrow One non-basic variable enters the basis and one basic variable leaves
 - ullet Start with basis $oldsymbol{B} = [oldsymbol{A}_{B(1)} \cdots oldsymbol{A}_{B(m)}]$
 - Variable $x_{B(l)}$ leaves the basis; variable x_j enters the basis
 - ullet Move to new basis $\overline{m{B}} = [m{A}_{B(1)} \cdots m{A}_{B(l-1)} m{A}_j m{A}_{B(l+1)} \cdots m{A}_{B(m)}]$

$$\begin{cases} d_j = 1 \\ d_i = 0 \\ d_B = - \boldsymbol{B}^{-1} \boldsymbol{A}_j \end{cases} \text{ for other non-basic variables } i \neq j \in \mathcal{N}$$

$$\theta^* = \min_{i=1,\cdots,m:d_{B(i)} < 0} \left(-\frac{x_{B(i)}}{d_{B(i)}} \right) = -\frac{x_{B(l)}}{d_{B(l)}}$$

Theorem

- ullet $\overline{B}=[m{A}_{B(1)}\cdotsm{A}_{B(l-1)}m{A}_jm{A}_{B(l+1)}\cdotsm{A}_{B(m)}]$ is a basis
- $y = x + \theta^* d$ is a BFS associated with basis \overline{B} .

Algorithm

- 1. Start with basis $B = [A_{B(1)}, \cdots, A_{B(m)}]$ and BFS x.
- 2. Compute $\bar{c}_i = c_i c_B^{\top} B^{-1} A_i$
 - If $\bar{c}_i \geq 0$ for all non-basic variables j, then x is optimal; STOP.
 - Else select non-basic variable j such that $\bar{c}_i < 0$; PROCEED.
- 3. Compute $u = B^{-1}A_i$.
 - If $u \leq 0$, then the cost is unbounded; STOP. Else, PROCEED.
- 4. $\theta^* = \min_{i=1,\cdots,m,u_i>0} \frac{x_{B(i)}}{u_{B(i)}}$. Let l be such that $\theta^* = \frac{x_{B(l)}}{u_{B(l)}}$
- 5. Form new basis: $[m{A}_{B(1)}\cdotsm{A}_{B(l-1)}m{A}_{j}m{A}_{B(l+1)}\cdotsm{A}_{B(m)}]$
- 6. Get new BFS: $y_i = \theta^*$, $y_{B(i)} = x_{B(i)} \theta^* u_i$ for all i
- 7. Go back to Step 2.
- \rightarrow The simplex algorithm proceeds iteratively, moving from one extreme point to an adjacent one until all reduced costs become non-negative

$$(LO): \quad \min_{oldsymbol{x} \in \mathcal{P}} \quad oldsymbol{c}^{ op} oldsymbol{x}, \quad ext{where } \mathcal{P} = \{oldsymbol{x} \in \mathbb{R}^n_+ : oldsymbol{A} oldsymbol{x} = oldsymbol{b} \}$$

Theorem

If $P \neq \emptyset$ and every BFS is nondegenerate, the simplex algorithm terminates after a finite number of iterations. At termination:

- ullet either we have found a basis B^* , with an optimal BFS x^*
- or we have found a direction d such that Ad=0, $d\geq 0$, $c^{\top}d<0$; the problem is unbounded (i.e., the optimal cost is $-\infty$)
- ullet If the algorithm stops with $\overline{c} \geq 0$ (Step 2), the solution is optimal
- ullet If the algorithm stops with $u \leq 0$ (Step 3), the problem is unbounded
- Otherwise, the cost strictly decreases at each iteration $(c^{\top}y < c^{\top}x)$, so the algorithm never revisits the same solution twice
- → Finite convergence due to the finite number of extreme points

Simplex method by example (1/3)

- Start from basic variable: $\boldsymbol{x} = (0, 0, 0, 20, 20, 20)$, with objective of 0
- Increase x_1 , as much as possible

$$\begin{cases} x_1 = 20 - 2x_2 - 2x_3 - x_4 \\ x_1 = 10 - 0.5x_2 - x_3 - 0.5x_5 \\ x_1 = 10 - x_2 - 0.5x_3 - 0.5x_6 \end{cases}$$

$$\implies x_1 = 10 - 0.5x_2 - x_3 - 0.5x_5$$

Plug into the problem formulation:

Simplex method by example (2/3)

- New basic variable: $\boldsymbol{x} = (10, 0, 0, 10, 0, 0)$, with objective of -100
- Increase x_3 , as much as possible

$$\begin{cases} x_3 = 10 - 1.5x_2 - x_4 + 0.5x_5 \\ x_3 = 10 - x_1 - 0.5x_2 - x_4 - 0.5x_5 \\ x_3 = x_2 + x_5 - x_6 \\ \implies x_3 = 10 - 1.5x_2 - x_4 + 0.5x_5 \end{cases}$$

Plug into the problem formulation:

Simplex method by example (3/3)

- New basic variable: $\boldsymbol{x}=(0,0,10,0,0,10)$, with objective of -120
- Increase x_2 , as much as possible

$$\begin{cases} x_2 = 6.67 - 0.67x_3 - 0.67x_4 + 0.33x_5 \\ x_2 = x_1 - x_4 + x_5 \\ x_2 = 4 - 0.4x_4 + 0.6x_5 - 0.4x_6 \\ \implies x_2 = 4 - 0.4x_4 + 0.6x_5 - 0.4x_6 \\ & \implies x_2 = 4 - 0.4x_4 + 0.6x_5 - 0.6x_6 \\ \text{s.t.} \end{cases} \\ \begin{array}{c} \mathbf{x}_3 + \mathbf{0.4}x_4 + \mathbf{0.4}x_5 - \mathbf{0.6}x_6 = 4 \\ x_1 - 0.6x_4 + 0.4x_5 + 0.4x_6 = 4 \\ x_2 + 0.4x_4 - 0.6x_5 + 0.4x_6 = 4 \\ \end{array}$$

- New basic variable: x = (4, 4, 4, 0, 0, 0), with objective of -136
 - No more possible improvement, hence optimal solution