

Lecture 4-4 : { Feasible-direction Method Penalty Method

노트 제목

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▣ Feasible-direction Method (Numerical Method for NLP with inequality constraints)

$$\min f(x)$$

$$\text{s.t. } g_i(x) \leq 0, \quad i=1, \dots, m$$

Approach:

- * Start with a feasible point x_k and determine which constraints are active
- * look for feasible-descent direction d_k (\rightarrow becomes linear programming)
- * 1-D search to find x_{k+1}
- * Repeat until convergence

Simplified Version

i) feasible-descent direction finding

$$\min \nabla f^T(x_k) d \quad \oplus \quad \nabla f^T d_k < 0$$

$$\text{s.t. } \nabla g_i^A(x_k) d \leq 0$$

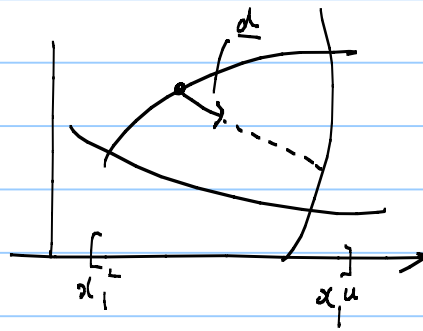
$$-1 \leq d_i \leq 1$$

\Rightarrow "LP" for (d_1, d_2, \dots, d_n)

$$\Rightarrow \text{OR} \quad \max \beta$$

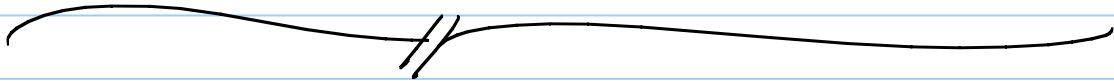
$$\text{s.t. } \begin{cases} \nabla f^T(x_k) d \leq -\beta \\ \nabla g_i^A(x_k) d \leq 0 \\ \beta > 0 \end{cases} \quad \Bigg\| \Rightarrow \text{LP for } d \text{ and } \beta$$

ii) 1-D search



$$\begin{aligned} \min_{\alpha} f(x_k + \alpha d) \\ \text{s.t. } g_i(x_k + \alpha d) \leq 0 \\ \Rightarrow \text{get } \alpha_k \end{aligned}$$

Detailed algorithm, see Vanderplaat or Belegundu.



- Penalty and Barrier Method
 - ↳ or Exterior Penalty Method
 - ↳ Interior Penalty Method

Idea: Treat constrained problems as approximate unconstrained problems

$$\text{Given } \left\{ \begin{array}{l} \min f(x) \quad x \in \mathbb{R}^n \\ \text{s.t. } g_i(x) \leq 0 \quad (i=1, \dots, m) \\ h_j(x) = 0 \quad (j=1, \dots, l) \end{array} \right. \quad \text{--- (A)}$$

$$\Omega = \{x \mid g(x) \leq 0, h=0\}$$

[1] Exterior Penalty Method
(simply called Penalty Method)

$$(A) \Rightarrow \min \phi(x; r) = f(x) + r P(x)$$

↑
not variables
but parameters

$$r = r_1, r_2, \dots, r_l \rightarrow \infty \quad (r_i \geq 0)$$

(Typical value of $r_i/r \approx 5$)

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Typical choice of $P(x)$:

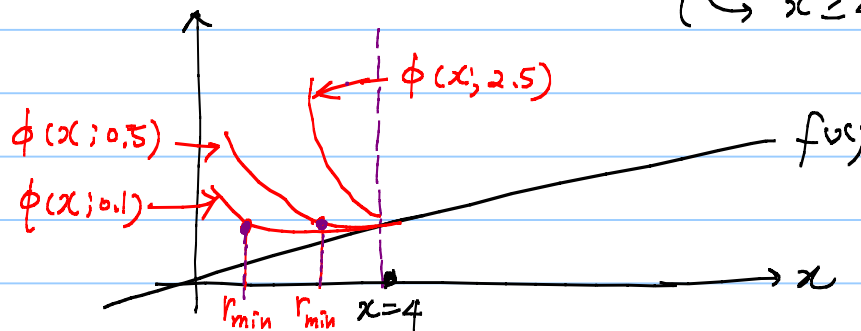
$$P(x) = \sum_{i=1}^m (\max[0, g_i(x)])^2 + \sum_{j=1}^l [h_j(x)]^2$$

($P > 0$ if any of constraints is violated!!)

$$\nabla P = 2 \sum_{i=1}^m \underbrace{\nabla g_i \max[0, g_i(x)]}_{\substack{\text{ignore discontinuities} \\ \text{at } g_i(x) = 0}} + 2 \sum_{j=1}^l \nabla h_j(x) h_j(x)$$

Case Study:

$$1) f(x) = 0.5x, \quad g_1(x) = 4 - x \leq 0 \quad (\hookrightarrow x \geq 4)$$



$$\begin{aligned} \phi(x; r) &= 0.5x + r P(x) \\ &= 0.5x + r \left\{ \max[0, (4-x)] \right\}^2 \end{aligned}$$

FoNC

$$\nabla \phi = \nabla f + r \nabla P = 0.5 + 2r \underbrace{(-1)}_{\substack{\uparrow \\ g'(x)}} \max[0, 4-x] = 0$$

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if $x \leq 4$

$$\nabla \phi = 0.5 - 2r(4-x) \equiv 0 \rightarrow 2rx = 8r - 0.5$$

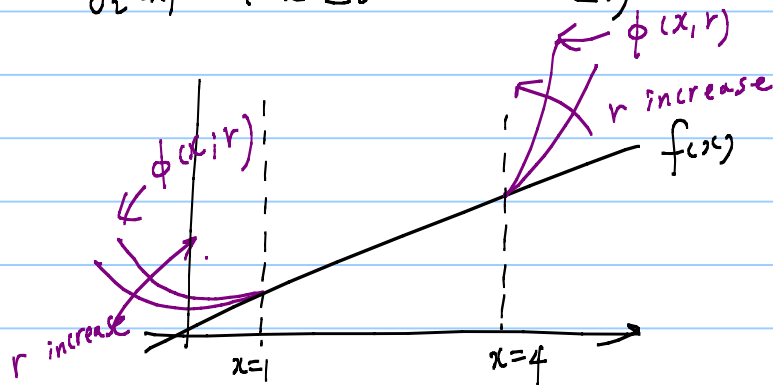
$$x_{\min} = \frac{1}{4r} (16r - 1) \rightarrow \begin{array}{l} 1.5 \text{ if } r = 0.1 \\ 3.5 \text{ if } r = 0.5 \\ \vdots \\ 4 \text{ if } r = \infty \end{array}$$

x_{\min} of ϕ approaches x_{\min} of f from the exterior of the feasible region \rightarrow "Exterior penalty method"

2) $f(x) = 0.5x$

$$g_1(x) = x - 4 \leq 0 \quad (\leftarrow x \leq 4)$$

$$g_2(x) = -x \leq 0 \quad (\leftarrow x \geq 1)$$



$$\phi(x; r) = f(x) + r \left\{ \begin{array}{l} [\max(0, x-4)]^2 \\ + [\max(0, 1-x)]^2 \end{array} \right\}$$

⑥

Example $\min f(x_1, x_2) = x_1^2 + 10x_2^2$
 s.t $h = 4 - x_1 - x_2 = 0$
 [exact Min = (3.636, 0.3636)]

Solve by the exterior penalty method

Sol: $\phi(x; r) = f(x_1, x_2) + r h(x_1, x_2)^2$
 $= x_1^2 + 10x_2^2 + r(4 - x_1 - x_2)^2$

FONC $\nabla \phi(x, r) = \begin{cases} 2x_1(1+r) + 2rx_2 - 8r \\ 2x_2(10+r) + 2rx_1 - 8r \end{cases} = \begin{cases} 0 \\ 0 \end{cases}$

$$x_1 = \frac{40r}{10+11r}; \quad x_2 = \frac{4}{10+11r}$$

r	(x ₁ , x ₂)	f	φ
1	(1.905, 0.1905)	3.992	7.619
10	(3.333, 0.3333)	12.220	13.333
100	(3.604, 0.3604)	14.288	14.144
1000	(3.633, 0.3633)	14.518	14.532

Check $H_\phi = \nabla^2 \phi$

$$= \begin{bmatrix} 2(1+r) & 2r \\ 2r & 2(10+r) \end{bmatrix}$$

→ becomes more and more ill-conditioned as $r \rightarrow \infty$

(Cause numerical problems with too large r's)

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Back to the Exterior Penalty Method:

Question: Solution Behavior $x^*(r)$ as
a ftn of penalty parameter

i) $x^*(r) \approx \underline{a} + \underline{b} r$ X

ii) $x^*(r) \approx \underbrace{(\underline{a})}_{\substack{\uparrow \\ \text{converged}}} + \frac{b}{r}$ --- (1) yes

Trick to improve the Solution Convergence

Use (1) with two values of r_{i-1} , and r_i

$$\begin{cases} x^*(r_{i-1}) = \underline{a} + \frac{b}{r_{i-1}} \\ x^*(r_i) = \underline{a} + \frac{b}{r_i} \end{cases}$$

$$\Rightarrow \underline{a} = \frac{\alpha x^*(r_{i-1}) - x^*(r_i)}{\alpha - 1}$$

$$\underline{b} = \left[\underline{a} x^*(r_{i-1}) - \underline{a} \right] r_{i-1}$$

where

$$\alpha = r_{i-1} / r_i$$

} Strategy A

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If Strategy A is applied to Example;

$r_1=1, r_2=10, \alpha=0.1$ [Exact $\underline{x}^* = (3.636, 0.3636)^T$]

$(x_i^* \triangleq x^*(r_i))$

$x_1^* = (1.905, 0.905)^T$ $x_2^* = (3.333, 0.3333)^T$

$\underline{a} = \{3.492, 0.3492\}$

↑ Better estimate

Convergence Criteria

- i) $\|\underline{x}_i^* - \underline{a}\| \leq \epsilon_1$ $\epsilon_1 = \text{small value} \times \|\underline{x}_i^*\|$
- OR ii) $|\phi - f| / f \leq \epsilon_2$
- OR iii) $|f_i^* - f_{i+1}^*| / |f_i^*| \leq \epsilon_3$

Lagrange Multiplier estimate at optimal pt: $(\nabla \phi = 0)$

$\mu_i \approx 2r \max [0, g_i]$

$\lambda_i \approx 2r h_j$

⑨

[2] Interior Penalty Method [Barrier Method]

$$\min \phi(x;r) = f(x) + \frac{1}{r} B_1(x) + r^{\frac{1}{2}} B_2(x)$$

$$r = r_1, r_2, \dots, r_n \rightarrow \infty \quad (r_n \rightarrow 0)$$

$$\text{s.t. } x \in \text{interior of } \Omega$$

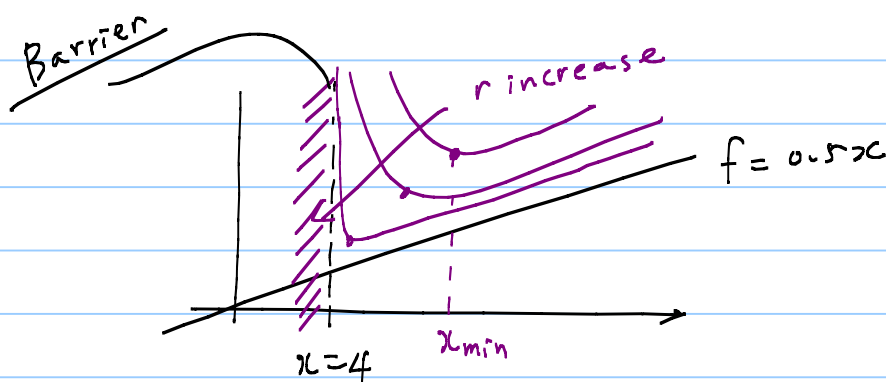
Typical functional forms of B_i

$$B_1(x) = - \sum_{i=1}^m \frac{1}{g_i(x)} \quad \leftarrow \text{Inverse Barrier function}$$

$$B_2(x) = \sum_{i=1}^l h_i^2(x)$$

example: $f(x) = 0.5x$ $g_1(x) = 4-x \leq 0$

$$\phi(x;r) = 0.5x - \frac{1}{r(4-x)}$$



① it produces a series of feasible solutions as r increases

② Thus, it requires a feasible starting point.