

LECTURE 8
PENALTY, BARRIER ~~AND~~
~~AUGMENTED LAGRANGIAN~~
METHODS

Penalty Method

(NEP) minimize $f(x)$
 $x \in \mathbb{R}^n$
 $c_j(x) = 0 \quad j \in E$

Penalty function

$$P(x; M) := f(x) + \frac{1}{2M} \sum_{j \in E} [c_j(x)]^2$$

↓
penalty
parameter
> 0

Idea

Solve

minimize $P(x; M)$
 $x \in \mathbb{R}^n$

repeatedly for various M , gradually
decreasing M to 0.

Ex

minimize x_2

$$x_1^2 - x_2 = 4$$

global
minimizer

$$x_* = (0, -4)$$

smallest value of objective
 $f(x_*) = -4$

Penalty function

$$P(x; \mathcal{M}) := x_2 + \frac{1}{2\mathcal{M}} (x_1^2 - x_2 - 4)^2$$

$$\nabla_x P(x; \mathcal{M}) = \begin{bmatrix} 2x_1(x_1^2 - x_2 - 4)/\mathcal{M} \\ 1 - (x_1^2 - x_2 - 4)/\mathcal{M} \end{bmatrix}$$

$$\nabla_{xx}^2 P(x; \mathcal{M}) = \begin{bmatrix} \frac{2(x_1^2 - x_2 - 4)}{\mathcal{M}} + \frac{4x_1^2(x_1^2 - x_2 - 4)}{\mathcal{M}} & -\frac{2x_1}{\mathcal{M}} \\ -\frac{2x_1}{\mathcal{M}} & \frac{1}{\mathcal{M}} \end{bmatrix}$$

x_* such that $\nabla_x P(x_*; \mathcal{M}) = 0$

$$x_*(\mathcal{M}) = (0, -4 - \mathcal{M}).$$

Furthermore,

$$\nabla_{xx}^2 P(x_*(\mathcal{M}); \mathcal{M}) = \begin{bmatrix} 2 & 0 \\ 0 & 1/\mathcal{M} \end{bmatrix}.$$

is PD. Thus

(i) $x_*(\mathcal{M})$ is a local min of $P(x; \mathcal{M})$,

(ii) $\lim_{\mathcal{M} \rightarrow 0^+} x_*(\mathcal{M}) = (0, -4) = x_*$

(2)

Pseudocode

Given $x_s^{(0)}$ and $M_1 > 0$.

for $k = 1, 2, 3, \dots$

(1) Choose a $\tau_k > 0$ (such that $\lim_{k \rightarrow \infty} \tau_k = 0$)

(2) Find $x_s^{(k)}$ such that

$$\| \nabla_x P(x_s^{(k)}; M_k) \| \leq \tau_k$$

by a (modified) Newton method with a line search starting from

$$x_s^{(0)} = x_s^{(k-1)}.$$

(3) Choose a $M_{k+1} \in (0, M_k)$ (such that $\lim_{k \rightarrow \infty} M_k = 0$)

end

THM

Let x_* be any limit point of $\{x_s^{(k)}\}$ such that LICQ holds at x_* . There exists λ_* such that (x_*, λ_*) satisfies KKT conditions for (NEP).

PROOF

Notice that

$$\nabla_x P(x; M) = \nabla f(x) + \frac{1}{M} \sum_{j \in E} c_j(x) \nabla c_j(x)$$

Exploiting $\|\nabla_x P(x_s^{(k)}, \mathcal{M}_k)\| \leq \tau_k$

$$\left\| \nabla_f(x_s^{(k)}) + \frac{1}{\mathcal{M}_k} \sum_{j \in E} c_j(x_s^{(k)}) \nabla c_j(x_s^{(k)}) \right\| \leq \tau_k$$

$$\Rightarrow \left\| \sum_{j \in E} c_j(x_s^{(k)}) \nabla c_j(x_s^{(k)}) \right\| \leq \mathcal{M}_k [\tau_k + \|\nabla_f(x_s^{(k)})\|]$$

Taking the limit as $k \rightarrow \infty$,

$$\sum_{j \in E} c_j(x_*) \nabla c_j(x_*) = 0.$$

Due to LICQ $c_j(x_*) = 0$ for each $j \in E$.

Next, letting $\lambda_j^{(k)}$ such that

$$\lambda_j^{(k)} := -c_j(x_s^{(k)}) / \mathcal{M}_k.$$

We claim that $\lim_{k \rightarrow \infty} \lambda_j^{(k)} = \lambda_j^*$ exists.

To see this, note

$$\nabla_x P(x_s^{(k)}, \mathcal{M}_k) = \nabla_f(x_s^{(k)}) + \frac{1}{\mathcal{M}_k} \sum_{j \in E} c_j(x_s^{(k)}) \nabla c_j(x_s^{(k)})$$

$$\Rightarrow \perp_E(x_s^{(k)})^T \lambda^{(k)} = \nabla_f(x_s^{(k)}) - \perp_E(x_s^{(k)})^T \lambda^{(k)}$$

$$\Rightarrow \lambda^{(k)} = \left[\perp_E(x_s^{(k)}) \perp_E(x_s^{(k)})^T \right]^{-1} \perp_E(x_s^{(k)}) \left[\nabla_f(x_s^{(k)}) - \nabla_x P(x_s^{(k)}, \mathcal{M}_k) \right]$$

$$\Rightarrow \lim_{k \rightarrow \infty} \lambda^{(k)} = \left[\perp_E(x_*) \perp_E(x_*)^T \right]^{-1} \perp_E(x_*) \nabla_f(x_*)$$

(4)

Consequently,

$$\left\| \nabla_f(x_s^{(k)}) - \sum_{j \in E} \lambda_j^{(k)} \nabla_{c_j}(x_s^{(k)}) \right\| \leq \tau_k$$

implying

$$\nabla_f(x_s^{(k)}) - \sum_{j \in E} \lambda_j^{(k)} \nabla_{c_j}(x_s^{(k)}) \rightarrow 0$$

as $k \rightarrow \infty$

$$\implies \nabla_f(x_*) - \sum_{j \in E} [\lambda_*]_j \nabla_{c_j}(x_*) = 0 \quad \square$$

Calculation of Newton step

$$\nabla_{xx}^2 P(x; \mathcal{M}) p = -\nabla_x P(x; \mathcal{M})$$

where

$$\nabla_x P(x; \mathcal{M}) = \nabla_f(x) + \frac{1}{\mathcal{M}} \sum_{j \in E} c_j(x) \nabla_{c_j}(x)$$

$$\nabla_{xx}^2 P(x; \mathcal{M}) = [\nabla_f(x)]' + \frac{1}{\mathcal{M}} \sum_{j \in E} [\nabla_{c_j}(x)]' c_j(x) +$$

$$\frac{1}{\mathcal{M}} \sum_{j \in E} \nabla_{c_j}(x) [c_j(x)]'$$

$$= \nabla_f^2(x) + \boxed{\frac{1}{\mathcal{M}} \sum_{j \in E} c_j(x) \nabla_{c_j}^2(x)} \quad \textcircled{1}$$

$$+ \boxed{\frac{1}{\mathcal{M}} \sum_{j \in E} \nabla_{c_j}(x) \nabla_{c_j}(x)^T} \quad \textcircled{2}$$

$$J_E(x)^T J_E(x)$$

① - Well-conditioned $\frac{-c_j(x)}{\mathcal{M}} \rightarrow \lambda_*$

② - ill-conditioned

Norm $\rightarrow \infty$ as $\mathcal{M} \rightarrow 0$

Singular if $|E| < n$

To avoid ill-conditioning due to (2)

$$q := \frac{1}{M} \mathcal{J}_E(x) p$$

\downarrow $m \times 1$ \downarrow $n \times 1$

Solve

$$\begin{bmatrix} \nabla_f^2(x) + \frac{1}{M} \sum_{j \in E} c_j(x) \nabla_{c_j}^2 & \mathcal{J}_E(x)^T \\ \mathcal{J}_E(x) & -M \mathbf{I}_m \end{bmatrix} \begin{bmatrix} p \\ q \end{bmatrix} = \begin{bmatrix} -\nabla_x P(x; M) \\ 0 \end{bmatrix}$$

$(m+n) \times (m+n)$

for p and q .

Conditioning of a linear system

$$\begin{array}{ccc} Ax = b & & \\ \downarrow & & \downarrow \\ n \times n & & n \times 1 \\ \text{invertible} & & \text{given} \\ \text{given} & & \end{array}$$

Perturbed system

$$(A + \Delta A)(x + \Delta x) = b$$

$$\cancel{Ax} + \Delta A x + A \Delta x + \Delta A \cdot \Delta x = \cancel{b}$$

$$\Delta x = (A + \Delta A)^{-1} \Delta A x$$

Now consider

$$\kappa := \limsup_{\Delta A \rightarrow 0} \frac{\|\Delta x\| / \|x\|}{\|\Delta A\| / \|A\|}$$

$$= \limsup_{\Delta A \rightarrow 0} \frac{\|A + \Delta A\|^{-1} \cancel{\|\Delta A\|} \cancel{\|x\|} / \cancel{\|x\|}}{\cancel{\|\Delta A\|} / \|A\|}$$

$$= \|A^{-1}\| \|A\|$$

$$\begin{array}{l} \text{if } A \text{ is symmetric} \\ \uparrow \\ = \lambda_{\max}(A) \quad \lambda_{\max}(A^{-1}) \end{array}$$

$$= \lambda_{\max}(A) / \lambda_{\min}(A)$$

Logarithmic Barrier Method

$$\begin{aligned} & \text{minimize} && f(x) \\ & x \in \mathbb{R}^n \\ & c_j(x) \geq 0 \quad j \in I \end{aligned}$$

Logarithmic Barrier function

$$L(x; M) = f(x) - M \sum_{j \in I} \ln c_j(x)$$

↓
Barrier
parameter

Idea

Start with a feasible x . Solve

$$\begin{aligned} & \text{minimize} && L(x; M) \\ & x \in \mathbb{R}^n \end{aligned}$$

repeatedly, letting $M \rightarrow 0$.

Ex

$$\begin{aligned} & \text{minimize} && x_1^2 + x_2^2 \\ & x \in \mathbb{R}^2 \\ & x_1 + x_2 \geq 1 \end{aligned}$$

$$\begin{aligned} x_* &= (1/2, 1/2) \\ \text{optimal objective} \\ f_* &= 1/2 \end{aligned}$$

$$L(x; \mu) = x_1^2 + x_2^2 - \mu \ln(x_1 + x_2 - 1)$$

$$\nabla_x L(x; \mu) = \begin{bmatrix} 2x_1 - \mu / (x_1 + x_2 - 1) \\ 2x_2 - \mu / (x_1 + x_2 - 1) \end{bmatrix}$$

$$\nabla_{xx}^2 L(x; \mu) = \begin{bmatrix} 2 + \frac{\mu}{(x_1 + x_2 - 1)^2} & \frac{\mu}{(x_1 + x_2 - 1)^2} \\ \frac{\mu}{(x_1 + x_2 - 1)^2} & 2 + \frac{\mu}{(x_1 + x_2 - 1)^2} \end{bmatrix}$$

An $x(\mu)$ such that $\nabla_x L(x(\mu); \mu) = 0$ is given by

$$x(\mu) = \left(\frac{1 + \sqrt{1 + 4\mu}}{2}, \frac{1 + \sqrt{1 + 4\mu}}{2} \right)$$

satisfies

$$\lim_{\mu \rightarrow 0^+} x(\mu) = \left(\frac{1}{2}, \frac{1}{2} \right) = x_*$$

Mixed Penalty Logarithmic Barrier
Method

minimize $f(x)$
 $x \in \mathbb{R}^n$

$$c_j(x) = 0 \quad j \in E$$

$$c_j(x) \geq 0 \quad j \in I$$

equivalently

minimize $f(x)$

x, s

$$c_j(x) = 0 \quad j \in E$$

$$c_j(x) - s_j = 0 \quad j \in I$$

↓ slack variables

$$s_j \geq 0 \quad j \in I$$

mixed penalty logarithmic barrier
function

$$\begin{aligned} M(x, s; M) = & f(x) + \frac{1}{2M} \sum_{j \in E} [c_j(x)]^2 \\ & + \frac{1}{2M} \sum_{j \in I} [c_j(x) - s_j]^2 \\ & - M \sum_{j \in I} \ln s_j \end{aligned}$$

Idea

Start with $s > 0$ and an arbitrary x
Solve

$$\begin{aligned} & \text{minimize } M(x, s; M) \\ & x, s \end{aligned}$$

for various M , gradually decreasing M
to 0.

Connection with primal-dual methods

Let us consider

$$\begin{aligned} \text{(NIP)} \quad & \text{minimize } f(x) \\ & x \in \mathbb{R}^n \\ & c_j(x) \geq 0 \quad j \in I \end{aligned}$$

and associated logarithmic-barrier function

$$L(x; \mu) = f(x) - \mu \sum_{j \in I} \ln c_j(x).$$

Consider $x(\mu)$ such that $\nabla_x L(x(\mu); \mu) = 0$.

$$\nabla f(x(\mu)) - \sum_{j \in I} \frac{\mu}{c_j(x(\mu))} \nabla c_j(x(\mu)) = 0.$$

$\lambda_j(\mu) :=$

Notice that $(x(\mu), \lambda(\mu))$ satisfies

- (KKT _{μ})
- (i) $\nabla_x L(x(\mu), \lambda(\mu)) = 0$
 - (ii) $c_j(x(\mu)) > 0 \quad j \in I$
 - (iii) ~~$\lambda_j(\mu) > 0$~~ $\lambda_j(\mu) > 0 \quad j \in I$
 - (iv) $c_j(x(\mu)) \lambda_j(\mu) = \mu$

Primal central-path

$$\{(x(\mu)) \mid \mu > 0, x(\mu) \text{ satisfies } \text{KKT}_\mu \text{ for some } \lambda(\mu)\}$$

Logarithmic-barrier method is a primal central-path following algorithm.

THM (Convergence)

Suppose the strictly feasible region F° for (NIP) is not empty. Suppose also that x_* is a point such that

(i) ~~KKT~~ ^{second order sufficient conditions} hold at x_*

for some λ_* ,

(ii) LICQ holds at x_* ,

(iii) strict complementarity holds at x_* .

Then the following ^{are} ~~is~~ true.

(1) There exists a ball $B(x_*, \delta)$ such that (i) $L(x; \mu)$ has a unique local minimizer $x(\mu) \in B(x_*, \delta)$; (ii) $\lim_{\mu \rightarrow 0^+} x(\mu) = x_*$.

(2) Defining $\lambda(\mu)$ by $\lambda_j(\mu) := \mu / c_j(x(\mu))$

$$\lim_{\mu \rightarrow 0^+} \lambda(\mu) = \lambda_*$$

Primal-dual interior point method framework

KKT conditions for (NIP)

but complementarity condition replaced by centrality condition.

$$(i) \quad \nabla f(x) - \sum_{j \in I} \lambda_j \nabla c_j(x) = 0$$

$$(ii) \quad c_j(x) \gg 0$$

$$(iii) \quad \lambda_j \gg 0$$

$$(iv) \quad c_j(x) \lambda_j = \mathcal{M}$$

equivalently

$$(i') \quad \nabla f(x) - \sum_{j \in I} \lambda_j \nabla c_j(x) = 0$$

$$(ii') \quad c_j(x) - s_j = 0$$

$$(iii') \quad \lambda_j \gg 0, \quad s_j \gg 0$$

$$(iv') \quad s_j \lambda_j = \mathcal{M}$$

Solve

(i'), (ii') and (iv')

by means of a Newton method.

Impose $\lambda_j, s_j > 0$ in a line search.

Gradually decrease $\mu \rightarrow 0^+$.

Newton's method is applied to

$$F: \mathbb{R}^{n+2m} \rightarrow \mathbb{R}^{n+2m}$$

$$F(x, \lambda, s) := \begin{bmatrix} \nabla f(x) - \sum_{j \in I} \lambda_j \nabla c_j(x) \\ c(x) - s \\ s \wedge e - \mu e \end{bmatrix}$$

Newton step

$$F'(x, \lambda, s) \begin{bmatrix} \Delta x \\ \Delta \lambda \\ \Delta s \end{bmatrix} = -F(x, \lambda, s)$$

$$\begin{bmatrix} \nabla_{xx}^2 \mathcal{L}(x, \lambda) & -J(x)^T & 0 \\ -J(x) & 0 & -I \\ 0 & s & \wedge \end{bmatrix} \begin{bmatrix} \Delta x \\ \Delta \lambda \\ \Delta s \end{bmatrix} = -F(x, \lambda, s)$$