

Lecture 7 2023-09-16

Last time: KKT conditions for inequality
constrained
optimization

Today: primal-dual interior point method
for convex quadratic programs

$$\min_x \quad \frac{1}{2} x^T P x + p^T x \quad P \in S_+^n \quad p \in \mathbb{R}^n$$

$$\text{subj. to: } \begin{aligned} Ax &= b & A \in \mathbb{R}^{m \times n}, b \in \mathbb{R}^m \\ Gx &\leq h & G \in \mathbb{R}^{P \times n}, h \in \mathbb{R}^P \end{aligned}$$

introduce slack variables: $s \geq 0 \quad s \in \mathbb{R}^P$

$$Gx \leq h \iff \begin{aligned} Gx + s &= h \\ s &\geq 0 \end{aligned}$$

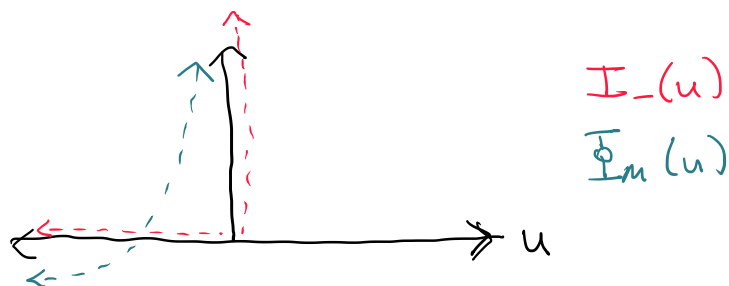
Want to enforce $s \geq 0 \rightarrow$ without Lagrange multipliers
 \rightarrow don't enforce $s \geq 0$ explicitly

→ don't enforce $s \geq 0$ explicitly

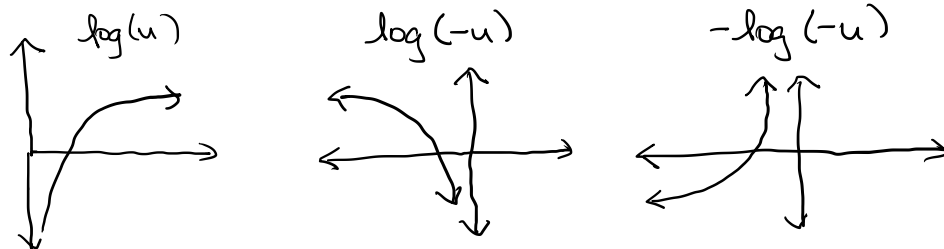
→ penalize violations to implicitly enforce $s \geq 0$

e.g. suppose we have some constraint $u \leq 0$

add penalty to violation: $I_-(u) = \begin{cases} 0 & \text{if } u \leq 0 \\ \infty & \text{otherwise} \end{cases}$



smooth approximation: $\bar{I}_m(u) = -\log(-u)$



→ if we have $s \geq 0$ $s \in \mathbb{R}^p$

$$\rightarrow \bar{\Phi}_m(-s) = -m \sum_{i=1}^p \log(s_i) \quad \text{where } m > 0$$

→ convert QP to barrier form:

$$\min_x \frac{1}{2} x^T P x + p^T x$$

$$\min_x \frac{1}{2} x^T P x + p^T x + \bar{\Phi}_m(-s)$$

$$\begin{array}{ccc}
 & \min_x & \\
 \text{subj. to: } & \begin{array}{c} Ax=b \\ Gx \leq h \end{array} & \iff \text{subj. to: } \begin{array}{c} Ax=b \\ Gx+s=h \\ s \geq 0 \end{array}
 \end{array}$$

NOTE: as $m \rightarrow 0$, recover original solution

How to solve this barrier-form QP?

→ write Lagrangian and take Taylor expansion

$$\mathcal{L}(x, s, y, z) = \frac{1}{2} x^T P x + p^T x + \frac{1}{m} \ln(-s) + y^T (Ax - b) + z^T (Gx + \underline{s} - h)$$

N.C.O:

$$(1) \nabla_x \mathcal{L}(x^*, s^*, y^*, z^*) = P x^* + p + A^T y^* + G^T z^*$$

$$(2) \nabla_y \chi(x^*, s^*, y^*, z^*) = Ax^* - b$$

$$(3) \nabla_z \chi(x^*, s^*, y^*, z^*) = Gx^* + s^* - h$$

$$(4) \nabla_s \chi(x^*, s^*, y^*, z^*) = z^* - Ms^{-1}$$

$$\Phi_M(-s) = -M \sum_{i=1}^p \log(s_i)$$

$$\nabla_s \Phi_M(-s) = -M s^{-1} = \begin{pmatrix} -M/s_1 \\ \vdots \\ -M/s_p \end{pmatrix}$$

$$\rightarrow r(x, s, y, z) = \begin{pmatrix} Px + p + A^T y + G^T z \\ s \odot z - M \\ Gx + s - h \\ Ax - b \end{pmatrix}$$

$$\text{Define: } D(s) = \begin{pmatrix} s_1 & \dots & s_p \end{pmatrix} \quad D(z) = \begin{pmatrix} z_1 & \dots & z_p \end{pmatrix}$$

Use same approach as last time: given $(\bar{x}, \bar{s}, \bar{y}, \bar{z})$,

take Taylor series expansion and solve

for $(\Delta x, \Delta s, \Delta y, \Delta z)$ to find $r(x^*, s^*, y^*, z^*) = 0$

$$\rightarrow r(x, s, y, z) \approx r(\bar{x}, \bar{s}, \bar{y}, \bar{z}) + \frac{\partial r}{\partial x} \Delta x + \frac{\partial r}{\partial s} \Delta s + \frac{\partial r}{\partial y} \Delta y + \frac{\partial r}{\partial z} \Delta z$$

compute partials:

$$\frac{\partial r}{\partial x} = \begin{pmatrix} P \\ 0 \\ G \\ A \end{pmatrix}$$

$$\frac{\partial r}{\partial s} = \begin{pmatrix} 1 & 0 & \dots & 0 \end{pmatrix}$$

$$\begin{pmatrix} \bar{z}_1 & \bar{s}_1 \end{pmatrix}$$

$$\begin{pmatrix} \bar{z}_1 & \bar{s}_1 \end{pmatrix}$$

$$\frac{\partial r}{\partial s} = \begin{pmatrix} 0 \\ D(\bar{z}) \\ I \\ 0 \end{pmatrix} \leftarrow \bar{z} \odot \bar{s} = \begin{pmatrix} s_1 \\ \vdots \\ \bar{z}_p \bar{s}_p \end{pmatrix} \rightarrow \frac{\partial r}{\partial s} = \begin{pmatrix} \vdots \\ \bar{z}_p \end{pmatrix} = D(\bar{z})$$

$$\frac{\partial r}{\partial z} = \begin{pmatrix} G^T \\ D(\bar{s}) \\ 0 \\ 0 \end{pmatrix} \quad \frac{\partial r}{\partial y} = \begin{pmatrix} A^T \\ 0 \\ 0 \\ 0 \end{pmatrix}$$

$$\Rightarrow \underbrace{\begin{pmatrix} P & 0 & G^T & A^T \\ 0 & D(\bar{z}) & D(\bar{s}) & 0 \\ G & I & 0 & 0 \\ A & 0 & 0 & 0 \end{pmatrix}}_{\text{KKT matrix}} \underbrace{\begin{pmatrix} \Delta x \\ \Delta s \\ \Delta z \\ \Delta y \end{pmatrix}}_{\text{Residual vector}} = - \underbrace{\begin{pmatrix} P\bar{x} + p + A^T\bar{y} + G^T\bar{z} \\ \bar{s} \odot \bar{z} - \mu \mathbf{1} \\ G\bar{x} + \bar{s} - h \\ A\bar{x} - b \end{pmatrix}}_{\text{(note minus sign in front)}}$$

NOTE: KKT matrix depends on \bar{s} and \bar{z} term,
so this linear system must be resolved at
each iteration

Primal-Dual Interior Point Method

1. Solve for (x^0, s^0, y^0, z^0) such that $s^0 \geq 0$ and $z^0 \geq 0$
for $k=1 \rightarrow N_{\max}$
2. Construct KKT matrix using $(x^{k-1}, s^{k-1}, y^{k-1}, z^{k-1})$
3. Compute residual vector using $(x^{k-1}, s^{k-1}, y^{k-1}, z^{k-1})$
4. Solve for affine step $(\Delta x_{\text{aff}}^k, \Delta s_{\text{aff}}^k, \Delta y_{\text{aff}}^k, \Delta z_{\text{aff}}^k)$

5. Solve for centering-corrector step $(\Delta x_{cc}^k, \Delta s_{cc}^k, \Delta y_{cc}^k, \Delta z_{cc}^k)$

6. Line search $\alpha > 0$ such that $s^k \geq 0$ and $z^k \geq 0$

$$x^k = x^{k-1} + \alpha (\Delta x_{aff}^k + \Delta x_{cc}^k)$$

$$s^k = s^{k-1} + \alpha (\Delta s_{aff}^k + \Delta s_{cc}^k) \geq 0$$

$$y^k = y^{k-1} + \alpha (\Delta y_{aff}^k + \Delta y_{cc}^k)$$

$$z^k = z^{k-1} + \alpha (\Delta z_{aff}^k + \Delta z_{cc}^k) \geq 0$$

7. if $\| \text{residual}(x^k, s^k, y^k, z^k) \|_2 \leq \epsilon_{tol}$
break

To recap:

1. Applied the generic N.C.O. from last time to a convex QP

2. Introduced a barrier function to enforce inequality constraints "implicitly" at each iteration
3. Derived N.C.O. for the Lagrangian corresponding to barrier QP-reformulation
4. Defined a residual function for these N.C.O. and derived KKT system