

## Lecture 6 2025-09-11

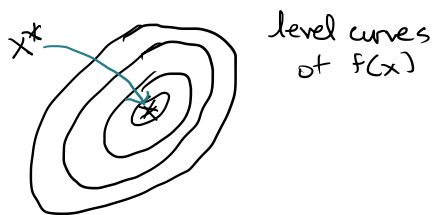
Last time: Newton's method with equality con.

Today: N.C.O. with inequality constraints

Review necessary conditions of optimality:

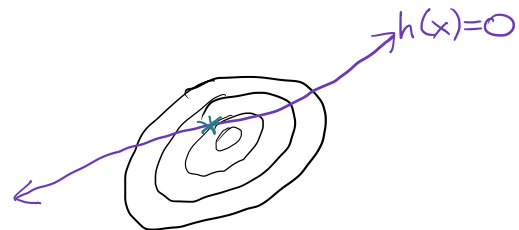
if  $x^*$  is an optimizer, then it must satisfy:

### Unconstrained Equality Constrained



$$\min_x f(x)$$

$f \in \mathbb{R}^2$



$$\min_x f(x)$$

subj. to:  $h(x)=0$

$f, h \in \mathbb{R}^2$

N.C.O.:

$$\nabla_x f(x^*) = 0$$

$$\nabla_x f(x^*) + y_i^* \nabla_x h_i(x^*) = 0$$

$$h_i(x^*) = 0$$

$\Downarrow$  succinctly

$$\mathcal{L}(x, y) = f(x) + y_i h_i(x)$$

$$\mathcal{L}(x, y) \begin{cases} \nabla_x \mathcal{L}(x^*, y^*) = 0 \\ \nabla_y \mathcal{L}(x^*, y^*) = 0 \end{cases}$$

Recall: for equality constrained optimization, invert

$$\text{KKT matrix: } \begin{pmatrix} H & A \\ A^T & 0 \end{pmatrix}$$

1.  $A$  is full rank
2. Hessian is positive definite  $\forall x$

e.g. quadratic program with equality

constraints

$$\begin{aligned} \min_x \quad & \frac{1}{2} x^T P x + p^T x \\ \text{subj. to:} \quad & Ax = b \end{aligned}$$

$$x \in \mathbb{R}^n$$

$$A \in \mathbb{R}^{m \times n} \quad b \in \mathbb{R}^m$$

$$P \in \mathcal{S}_+^n \quad (\text{i.e. } P \text{ is a positive definite matrix of size } \mathbb{R}^{n \times n})$$

$\rightarrow$  this ensures  $\nabla_{xx} f(x)$  is positive definite

$$\mathcal{L}(x, y) = \frac{1}{2} x^T P x + p^T x + y^T (Ax - b)$$

$$\rightarrow \nabla_x \mathcal{L}(x, y) = Px + p + A^T y := 0$$

$$\nabla_y \mathcal{L}(x, y) = Ax - b := 0$$

given  $x^{(0)}$  s.t.  $Ax^{(0)} - b = 0$ , can use feasible-start

Newton method:

$$\nabla_x f(x) = Px + p \quad \nabla_{xx} f(x) = P$$

$$\Rightarrow \begin{pmatrix} P & A^T \\ A & 0 \end{pmatrix} \begin{pmatrix} \Delta x \\ y \end{pmatrix} = - \begin{pmatrix} P x^{(k)} + p \\ 0 \end{pmatrix}$$

Optimization with linear inequality constraints

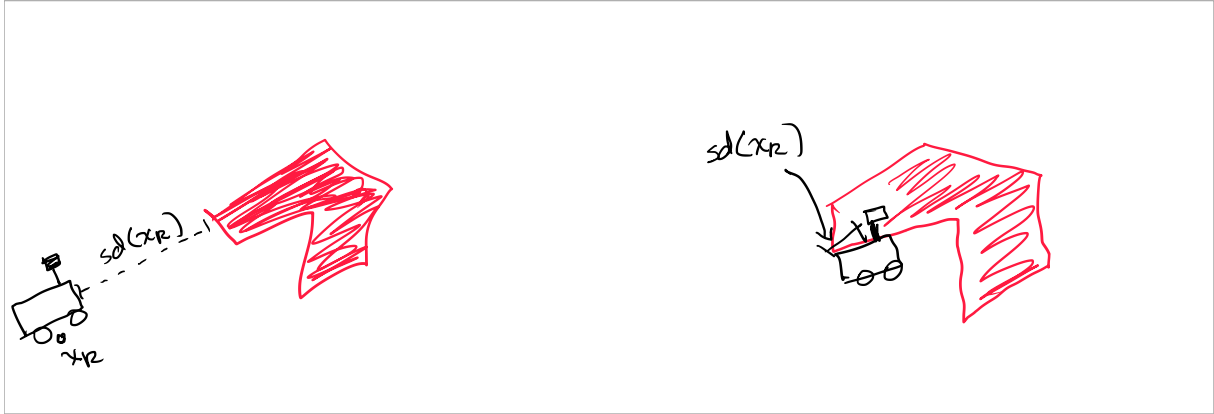
start with nonlinear form:

$$\begin{aligned} \min_x & f(x) \\ \text{subj. to: } & g_c(x) \leq 0 \quad c = 1, \dots, p \end{aligned}$$

e. g. practical examples  $u_k \leq u_{\max} \quad u \in \mathbb{R}^{n_u}$

$$u_{\min} \leq u_k \rightarrow u_{\min} - u_k \leq 0$$

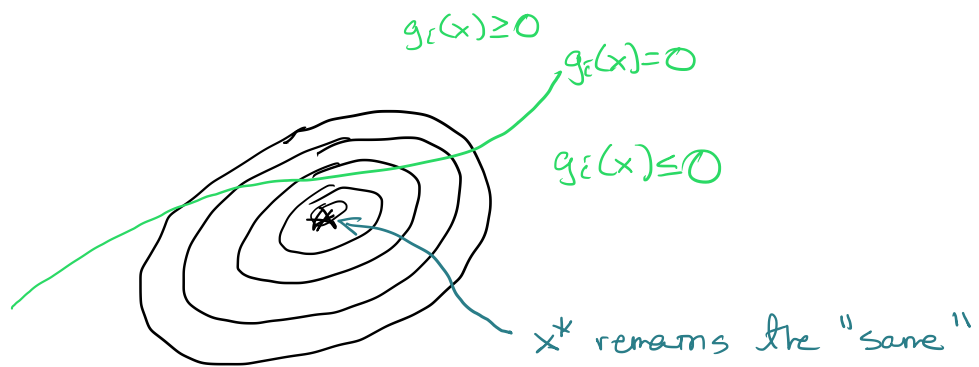
signed distance field:  $sd(x_p) \geq r \rightarrow r - sd(x_p) \leq 0$



How do we get necessary conditions of optimality?

two cases:

1.  $g_L(x) \leq 0$  doesn't affect  $x^*$

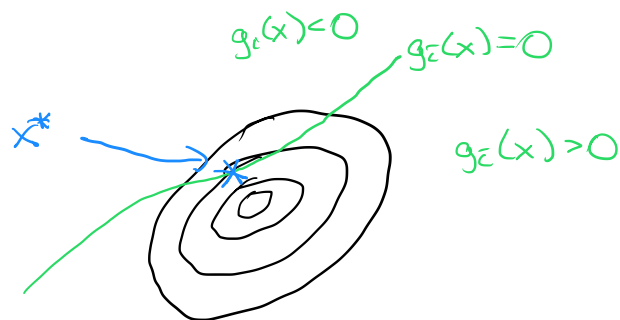


if  $g_c(x^*) < 0$  (i.e. constraint is inactive)

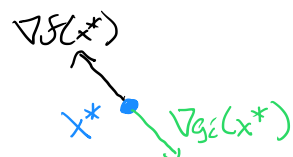
$$\rightarrow \nabla_x f(x^*) = 0$$

2.  $g_c(x) \leq 0$  "influences"  $x^*$

$\rightarrow g_c(x^*)$  is active



"similar" constraint as last time:



$$\nabla_x f(x^*) = -z_i \nabla_x g_i(x^*)$$

where  $z_i > 0$

$$\text{if } g_i(x^*) = 0$$

$$\rightarrow \nabla_x f(x^*) + z_i \nabla_x g_i(x^*) = 0$$

$$z_i > 0$$

Putting this together:

$$\text{if } g_i(x^*) = 0$$

// constraint

active

$$\nabla_x f(x^*) + z_i \nabla_x g_i(x^*) = 0$$

else

// constraint

inactive

$$\nabla_x f(x^*) = 0$$

use complementarity constraint to put this succinctly:

$$(1) \quad z_i^* \cdot g_i(x^*) = 0$$

$$(2) \quad \nabla f(x^*) + z_i \nabla g_i(x^*) = 0$$

$$(3) \quad g_i(x^*) \leq 0$$

This yields:

$$\text{if } g_i(x^*) < 0$$

$$\text{to satisfy (1), } z_i^* = 0$$

$$\text{then plug into (2), } \nabla f(x^*) = 0$$

else

$$g_i(x^*) = 0$$

$$\nabla f(x^*) + z_i \nabla g_i(x^*) = 0$$

$$z_i > 0$$

N. L.O. for inequality constrained optimization:

$$\mathcal{L}(x, y) = f(x) + \sum_{i=1}^p z_i g_i(x)$$

$$1. \quad \nabla_x \mathcal{L}(x^*, z^*) = \nabla_x f(x^*) + \sum_{i=1}^p z_i^* \nabla_x g_i(x^*) = 0$$



$$2. \quad \nabla_{z_i} \mathcal{L}(x^*, z^*) = g_i(x^*) \leq 0 \quad i=1, \dots, p$$

$$3. \quad z_i^* \cdot g_i(x^*) = 0 \quad i=1, \dots, p$$

$$4. \quad z_i^* \geq 0 \quad i=1, \dots, p$$

Add back  $m$  equality constraints:

$$\min_x f(x) \quad f, g, h \in \mathcal{C}^2$$

$$\text{subj. to: } g_i(x) \leq 0 \quad i=1, \dots, p$$

$$h_i(x) = 0 \quad i=1, \dots, m$$

$$\mathcal{L}(x, y, z) = f(x) + \sum_{i=1}^m y_i h_i(x) + \sum_{i=1}^p z_i g_i(x)$$

$$1. \nabla_x \mathcal{L}(x^*, y^*, z^*) = \nabla_x f(x) + \sum_{i=1}^m y_i^* \nabla_x h_i(x^*) + \sum_{i=1}^p z_i^* \nabla_x g_i(x^*) := 0$$

$$2. \nabla_{y_i} \mathcal{L}(x^*, y^*, z^*) = h_i(x^*) = 0 \quad i=1, \dots, m$$

$$3. \nabla_{z_i} \mathcal{L}(x^*, y^*, z^*) = g_i(x^*) \leq 0 \quad i=1, \dots, p$$

$$4. z_i^* \cdot g_i(x^*) = 0 \quad i=1, \dots, p$$

$$5. z_i^* \geq 0 \quad i=1 \dots p$$

5.

$$z_i^* \geq 0$$

$$i=1, \dots, p$$

$y$  &  $z$  are often called **dual** variables  
 $x$  is the **primal** variable

Quadratic program with equality + inequality constraints

$$\begin{aligned} \min_x \quad & \frac{1}{2} x^T P x + p^T x \quad P \in S_+^n \quad p \in \mathbb{R}^n \\ \text{subj. to:} \quad & A x = b \quad A \in \mathbb{R}^{m \times n}, \quad b \in \mathbb{R}^m \\ & G x \leq h \quad G \in \mathbb{R}^{p \times n} \quad h \in \mathbb{R}^p \end{aligned}$$

to solve this, we'll introduce slack variable  $s \geq 0$ :

$$G x \leq h \iff \begin{aligned} G x + s &= h \\ s &\geq 0 \quad s \in \mathbb{R}^p \end{aligned}$$

use line searches to ensure  $s \geq 0$  and  $z \geq 0$

$$\mathcal{L}(x, y, z, s) = \frac{1}{2} x^T P x + p^T x + y^T (A x - b) + z^T (G x + s - h)$$