

2/19: KKT Conditions & Lagrangians

Announcements:

- Project proposals due today, 2/19
- groups of ≤ 3
- 1pg. max, excluding ref.
- HW2 out, due 3/5

Today:

- constraints via projection
- Lagrange multipliers
- KKT
- Augmented Lagrangian methods

Last time:

$$\begin{aligned} \min_{x \in \mathbb{R}^n} & f(x) \\ \text{s.t.} & h_i(x) = 0 \quad i=1, \dots, l \\ & g_j(x) \leq 0 \quad j=1, \dots, m \end{aligned}$$

constrained optimization

Option 1: Reformulate

Find $T(\hat{x})$ where $h_i(T(\hat{x})) = 0$
 $g_j(T(\hat{x})) \leq 0$

Then we can solve an unconstrained problem

$$\min_{\hat{x}} f(T(\hat{x}))$$

Option 2: Project key idea: reproject onto X

$x_{k+1} = \Pi_X(x_{unc})$ (unconstrained step)
 $x_{k+1}^* = \hat{x}_k$

$$X = \{x \in \mathbb{R}^n \mid h(x) = 0, g(x) \leq 0\}$$

$$\Pi_X(x_{unc}) = \arg \min_{x \in X} \|x - x_{unc}\|_2$$

works well when X has a simple projection

e.g.1 [box constraints]

$$\min f(x)$$

$$\text{s.t. } l \leq x \leq u$$

$$\begin{bmatrix} l_1 \\ l_2 \end{bmatrix} \leq \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \leq \begin{bmatrix} u_1 \\ u_2 \end{bmatrix}$$

$$\Pi_X(x)_i = \begin{cases} l_i, & x_i \leq l_i \\ x_i, & l_i \leq x_i \leq u_i \\ u_i, & \text{otherwise} \end{cases} \quad \text{np. clamp}(x_i, l_i, u_i)$$

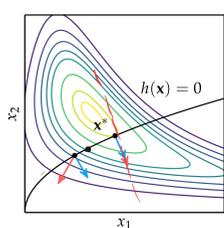
Q: How do we define constrained minima?

Consider a single equality constraint

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

$$\text{s.t. } h(x) = 0$$

An optimal point x^* requires:
 $h(x^*) = 0$
 $\nabla f(x^*) = -\lambda \nabla h(x^*), \lambda \in \mathbb{R}$



Lagrangian:

$$\mathcal{L}(x, \lambda) = f(x) + \lambda h(x)$$

$$\nabla_x \mathcal{L}(x^*, \lambda^*) = 0 = \nabla f(x^*) + \lambda^* \nabla h(x^*)$$

$$\nabla_\lambda \mathcal{L}(x^*, \lambda^*) = 0 = h(x^*)$$

For the multivariate case, $\lambda = [\lambda_1, \lambda_2, \dots, \lambda_l]$

$$\mathcal{L}(x, \lambda) = f(x) + \lambda^T h(x)$$

NOC: $\nabla_x \mathcal{L}(x^*, \lambda^*) = 0, \nabla_\lambda \mathcal{L}(x^*, \lambda^*) = 0$

$$\nabla f(x^*) + \sum_{i=1}^l \lambda_i^* \nabla h_i(x^*) = 0$$

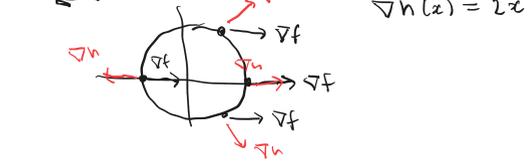
↑ linear combination

e.g.1 (optim. on unit circle)

$$\min_{x \in \mathbb{R}^2} e_1^T x$$

$$\text{s.t. } x^T x - 1 = 0$$

$$x^* = \begin{bmatrix} -1 \\ 0 \end{bmatrix} \quad x^* = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$



Inequality constraints

inactive

$g(x^*) < 0$
 $\nabla f(x^*) = 0$

active

$g(x^*) = 0$
 $\nabla f(x^*) = -\mu \nabla g(x^*) \text{ for } \mu \geq 0$

$$\mathcal{L}(x, \mu) = f(x) + \mu g(x)$$

NOC: $\nabla_x \mathcal{L}(x^*, \mu^*) = 0$
 $\nabla_\mu \mathcal{L}(x^*, \mu^*) = g(x^*) \leq 0$
 $\mu \geq 0$
 $\mu \cdot g(x^*) = 0$

Def) First-order constrained NOC (KKT)

For a constrained (smooth) problem N&W Ch. 12

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

$$\text{s.t. } h_i(x) = 0 \quad i=1, \dots, l$$

$$g_j(x) \leq 0 \quad j=1, \dots, m$$

For a minimum x^* of this problem, there must exist $\lambda^* \in \mathbb{R}^l, \mu^* \in \mathbb{R}^m$ satisfying

- stationarity: $\nabla f(x^*) + \sum_{i=1}^l \lambda_i^* \nabla h_i(x^*) + \sum_{j=1}^m \mu_j^* \nabla g_j(x^*) = 0$
- Feasibility: $h(x^*) = 0$
 $g(x^*) \leq 0$
- Dual feasibility: $\mu^* \geq 0$
- complementarity: $\mu^* \circ g(x^*) = 0$ ($\mu_j^* = 0, \text{ or } g_j(x^*) = 0$)

These are sometimes called Karush-Kuhn-Tucker (KKT) conditions.

$$\mathcal{L}(x, \lambda, \mu) = f(x) + \lambda^T h(x) + \mu^T g(x)$$

$$\max_{\lambda, \mu \geq 0} d(\lambda, \mu) = \arg \min_x \mathcal{L}(x, \lambda, \mu) \quad \text{"dual"}$$

Summary:

- when solving constrained problems:
1. Reformulate
 2. Project Π_X
 3. Lagrangian / multipliers