

Finite Dimension (*All SONC contain FONC, f, g, h C^1 in FONC, C^1 in SONC)

- Unconstrained - $\min f(x): (\Omega, \mathbb{R})$
 FONC: local min $\Rightarrow \nabla f(x_0) \cdot v \geq 0$ for all feasible v .
 Ω open \Rightarrow all v feasible, $\nabla f(x_0) = 0$
 (feasible: $x_0 + \epsilon v \in \Omega$ for small $\epsilon > 0$)
 SONC: local min $\Rightarrow \nabla f(x_0) \cdot v = 0 \Rightarrow v^T \nabla^2 f(x_0) v > 0$ for all feasible v .
 Ω open $\Rightarrow \nabla^2 f(x_0) \succ 0$
 SOS: $\nabla f(x_0) = 0, \nabla^2 f(x_0) \succ 0 \Rightarrow$ strict local min.
- Equality Constraint - $\min f(x)$ with $h_i(x) = 0$ (Ω open, x_0 regular)
 Regular: $\{\nabla h_i(x_0)\}$ linearly independent, interior points are regular.
 FONC: local min $\Rightarrow \exists \lambda_i \in \mathbb{R}$ s.t. $\nabla f + \lambda_i \nabla h_i = 0$ (Lagrange Multipliers)
 SONC: local min $\Rightarrow \exists \lambda_i \in \mathbb{R}$ s.t. $\nabla^2 f + \lambda_i \nabla^2 h_i \succ 0$ on $T_{x_0} M$
 $M = \{x \in \mathbb{R}^n \mid h_i(x) = 0\}$, $T_{x_0} = \{v \in \mathbb{R}^n \mid \nabla h_i(x_0) \cdot v = 0\}$
 $Q \succ 0$ on $T_{x_0} M \Leftrightarrow v^T Q v > 0 \forall v \in T_{x_0} M$ ($T_{x_0} M = T_{x_0}$ for x_0 regular)
 SOS: $\exists \lambda_i \in \mathbb{R}$ s.t. $\nabla f + \lambda_i \nabla h_i = 0, \nabla^2 f + \lambda_i \nabla^2 h_i \succ 0$ on $T_{x_0} M \Rightarrow$ strict local min.
- Inequality Constraint - $\min f(x)$ with $h_i(x) = 0, g_j(x) \leq 0$ (Ω open, x_0 regular)
 x_0 is regular if $\{\nabla h_i(x_0), \nabla g_j(x_0) \text{ active}\}$ linearly independent.
 (active: $g_j = 0$, inactive: $g_j < 0$)
 KT-condition: local min $\Rightarrow \exists \lambda_i \in \mathbb{R}, \mu_j \in \mathbb{R}$ s.t. $\nabla f + \lambda_i \nabla h_i + \mu_j \nabla g_j = 0$
 (if g_j inactive, then $\mu_j = 0$)
 SONC: local min $\Rightarrow \exists \lambda_i \in \mathbb{R}, \mu_j \in \mathbb{R}$ s.t. $L = \nabla^2 f + \lambda_i \nabla^2 h_i + \mu_j \nabla^2 g_j \succ 0$ on $T_{x_0} M$
 $T_{x_0} = \{v \in \mathbb{R}^n \mid \nabla h_i(x_0) \cdot v = 0, \nabla g_j(x_0) \cdot v = 0 \text{ with } g_j \text{ active}\}$
 SOS: x_0 feasible, $\exists \lambda_i \in \mathbb{R}, \mu_j \in \mathbb{R}$ s.t. L satisfy KT
 $L = \nabla^2 f + \lambda_i \nabla^2 h_i + \mu_j \nabla^2 g_j \succ 0$ on $T_{x_0} M$
 $T_{x_0} = \{v \in \mathbb{R}^n \mid \nabla h_i(x_0) \cdot v = 0, \nabla g_j(x_0) \cdot v = 0 \text{ with } g_j \text{ active, } \mu_j > 0\}$

Algorithms ($\frac{1}{2} x^T Q x - b^T x$)

- Method of gradient descend
 $x_{k+1} = x_k - \alpha_k \nabla f(x_k)$ $\alpha_k = \frac{\|\nabla f(x_k)\|^2}{\nabla f(x_k)^T Q \nabla f(x_k)}$
 Remark: $f(x_{k+1}) < f(x_k)$
 $(x_{k+1} - x_k) \cdot (x_{k+1} - x_k) = 0$
 $f: \mathbb{R}^n \rightarrow \mathbb{R} = \frac{1}{2} x^T Q x - b^T x$
 $\nabla f = Qx - b$, $\nabla^2 f = Q$, $A^T b$ is global min.
- Method of conjugate directions
 $x_{k+1} = x_k + \alpha_k d_k$ $\alpha_k = -\frac{\nabla f(x_k) \cdot d_k}{d_k^T Q d_k}$
 where $\{d_i\}$ is non-zero Q -orthogonal set.
 Q -orthogonal set: $d_i^T Q d_j = 0 \forall i \neq j$
 Remark: Q symmetric \Rightarrow exist Q -eigenbasis.
 eigenvectors of Q are Q - \perp vectors are linearly independent.

Local/Global min: small neighbourhood / for all x
 Non-strict/Strict: $f(x_0) \leq f(x) / f(x_0) < f(x)$
 Pos-def: $A > 0 \Leftrightarrow x^T A x > 0 \forall x \neq 0 \Leftrightarrow$ all eigenvalues > 0
 Pos semi-def: ≥ 0 instead of > 0

Infinite Dimension (Equality)

- No constraint: $-\frac{d}{dx} L p_i + L z_i = 0$
- Type 1: Isoperimetric - $\min F(u) = \int_a^b f(x) dx$ with $G(u) = \int_a^b g(x) dx$
 Write $L^F(x, z_i, p_i), L^G(x, z_i, p_i)$
 E.L. $-\frac{d}{dx} (L^F + \lambda L^G) + (L^F + \lambda L^G) z_i = 0$
 - Type 2: Holonomic - $\min F(u) = \int_a^b f(x) dx$ with $H(u) = c$
 Write $L(x, z_i, p_i), L z_i, L p_i, H u_i$
 E.L. $(-\frac{d}{dx} L p_i + L z_i) + \lambda(x) \cdot H u_i = 0$
- Testing function: all $C^1([0, 1] \rightarrow \mathbb{R}), v(0) = v(1) = 0$
 Theorem of CV: g cts. $[a, b], \int_a^b g(x) v(x) dx = 0 \forall v(x)$, then $v(x) = 0$.
- Basic ODEs
 $u''(x) = 0: u(x) = C$ $u''(x) = u(x): u(x) = Ae^x + Be^{-x}$
 $u''(x) = 0: u(x) = Ax + B$ $u''(x) = -u(x): u(x) = A \cos x + B \sin x$
 $u'(x) = u(x): u(x) = Ae^x$

Convexity & Subdifferentials

- Convex set: $sx_1 + (1-s)x_2 \in \Omega \forall x_1, x_2$
 Convex func: $f(sx_1 + (1-s)x_2) \leq sf(x_1) + (1-s)f(x_2) \forall x_1, x_2, s \in [0, 1]$
 Properties: f, g convex, $a > 0 \Rightarrow f + ag$ convex, $a f$ convex
 sublevel set $\{x \in \Omega \mid f(x) \leq c\}$ convex
- In C^1 , f convex $\Leftrightarrow f(y) \geq f(x) + \nabla f(x) \cdot (y-x) \forall x, y$
 In C^1 , f convex $\Leftrightarrow \nabla^2 f(x) \succ 0 \forall x$
- Ω compact, f convex attain max on $\Omega \Rightarrow \max_{\Omega} f$ on boundary
- subdiff v at $x_0: f(x) \geq f(x_0) + v \cdot (x - x_0) \forall x$
 subgrad $\partial f(x_0)$: set of all subdiff ($\partial f(x_0)$ is closed and convex)
- $\partial(a f) = a \partial f, a \geq 0$
 $h(x) = f(Ax + b)$ convex $\Rightarrow \partial h(x_0) = A^T \partial f(Ax_0 + b)$
 $f = \sum f_i, f_i$ convex $\Rightarrow \partial f = \sum \partial f_i$ ($A+B = \{a+b, a \in A, b \in B\}$)
 $f = \max\{f_i\}, f_i$ convex $\Rightarrow \partial f(x_0) = \cup \partial f_i(x_0)$ s.t. $f_i = f$
- Constrained Optimization - $\min f(x), x \in C$ convex
 Let $g(x) = f(x) + \delta_C(x)$ (indicator func = 0 if $x \in C, = \infty$ otherwise)
 x_0 minimize $f \Leftrightarrow x_0$ minimize $g \Leftrightarrow 0 \in \partial g(x_0)$
- Convex Programming - $\min f(x), x \in C = \{g_i(x) \leq 0\}, f, g$ convex
 If C has interior points (Slater), then
 $x_0 \in \mathbb{R}$ is optimal $\Leftrightarrow \exists y \in \partial f(x_0), \mu_i \geq 0$ s.t. $\begin{cases} -y = \sum \mu_i \partial g_i(x_0) \\ \mu_i g_i = 0 \end{cases}$