

## §4.1 Optimization Problems

"NLP" form ("Nonlinear Programming")

$$\min_{x \in \mathbb{R}^n} f_0(x) \quad \text{such that} \quad f_i(x) \leq 0 \quad i=1, \dots, m$$

"s.t."

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

Optimal value denoted  $p^*$

( $p^* = +\infty$  means infeasible)

= not assuming convexity yet =

If  $f_0(x) = \text{constant}$ , this is a "feasibility problem"

Sometimes you have to work a bit to put a problem in a standard form (eg.  $\max f_0 \iff -\min -f_0$   
or  $3x \geq 5 \iff 5 - 3x \leq 0$ )

Equivalent problems means problems w/ same argmin, but otherwise may be different

ex

$$\min \|Ax - b\|_2 \quad \text{vs} \quad \min \|Ax - b\|^2$$

↑ not even  
differentiable

↑ smooth  
(strongly smooth!)

### Tricks

change of variables (often affine)

$$\text{Ex: } \min_{x \in \mathbb{R}^1_{++}} \varphi(x) \quad \xLeftrightarrow{y = 1/x} \min_{y \in \mathbb{R}^1_{++}} \tilde{\varphi}(y) := \varphi(1/y)$$

$$\text{Ex: } \min_{x \in \mathbb{R}^1_+} \varphi(x) \quad \xLeftrightarrow{y = \sqrt{x}} \min_{y \in \mathbb{R}} \tilde{\varphi}(y) := \varphi(y^2)$$

$y \in \mathbb{R}$  unconstrained!

## Slack variables

$$\begin{aligned} \min \quad & f_0(x) \\ \text{s.t.} \quad & x \in \mathbb{R}^n \quad f_i(x) \leq 0 \quad i=1, \dots, m \end{aligned}$$

$$\begin{aligned} \Leftrightarrow \quad & \min \quad f_0(x) \\ & x \in \mathbb{R}^n, s \in \mathbb{R}^m \quad \text{s.t.} \quad f_i(x) + s_i = 0, \quad i=1, \dots, m \\ & s_i \geq 0, \quad i=1, \dots, m \end{aligned}$$

"s" is a "slack var."

## Eliminate Constraints

Ex Suppose  $Ax = b$  is a constraint  
 $\Rightarrow x = x_0 + y$  for some  $y \in \text{Ker}(A)$  ( $Ay = 0$ )  
and a "particular" solution  $x_0$   
( $Ax_0 = b$ . Any such  $x_0$  not works)

Let  $F$  be a matrix whose columns are a basis for  $\text{ker}(A)$ , then  $v = F \cdot z$  for some  $z$

$$\left( \text{ie. if } A = \underset{\text{SVD}}{\begin{bmatrix} u_1 & u_2 \end{bmatrix}} \begin{bmatrix} \Sigma & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} v_1^T \\ v_2^T \end{bmatrix}, \text{ then } F = V_2^T \right)$$

$\uparrow$   
0 sing. values

$$\begin{aligned} \text{then} \quad \min_x \quad & f_0(x) \\ \text{s.t.} \quad & Ax = b \end{aligned} \quad \Leftrightarrow \quad \min_z \quad f_0(x_0 + Fz)$$

(unconstrained!)

## Epigraph trick

$$\min_{x \in C} f_0(x) \iff \min_{x \in C, t \in \mathbb{R}} t \quad \text{s.t.} \quad f_0(x) \leq t$$

$$\min_{x \in \mathbb{R}^n} \|Ax - b\|_1 \left( := \sum_{i=1}^m |a_i^T x - b_i| \right)$$

$$\iff \min_{x \in \mathbb{R}^n, t \in \mathbb{R}^m} \sum_{i=1}^m t_i \quad \text{s.t.} \quad |a_i^T x - b_i| \leq t_i \quad \forall i=1, \dots, m$$

} aka  $\mathbb{1}^T t$  where  $\mathbb{1}$  is ones vector

## Misc. Tricks

$$\min_x f(x) + g(x) \iff \min_{x, z} f(x) + g(z) \quad \text{s.t.} \quad x = z$$

marginalization aka variable projection

$$\min_{x, z} f(x, z) \iff \min_x \left[ \min_z f(x, z) \right] = \min_x g(x)$$

$\underbrace{\hspace{10em}}_{g(x)}$

## §4.2 Convex optimization problems

NLP form

$$\min f_0(x)$$

→ require  $f_0$  to be a convex function

$$f_i(x) \leq 0$$

→ require  $f_i$  to be a convex function

$$h_i(x) = 0$$

$$\triangle f_i(x) \geq 0$$

↑  
i.e.  $h_i(x) \leq 0$  AND  $h_i(x) \geq 0$

( $f_i$  convex) is not a convex set.

so need  $h_i$  and  $-h_i$  convex

i.e.  $h_i$  must be affine, notation:  $a_i^T x = b_i$

Recall... (w/ <sup>non-empty, closed</sup> convex constraints)

$f_0$  convex  $\Rightarrow$  all local sol'n also global

$f_0$  strictly conv  $\Rightarrow$  global sol'n is unique

$f_0$  coercive  $\Rightarrow$  global sol'n exists

### ① Optimality conditions

let  $C = \{x: f_i(x) \leq 0 \ \forall i=1, \dots, n \text{ and } a_i^T x \leq b_i \ i=1, \dots, p\}$

$\min_{x \in C} f(x)$  ← assume conv fcn

← assume conv set

By convexity,  $\exists$  a subgradient at  $x$   $d \in \partial f(x)$

$$\forall y \quad f(y) \geq f(x) + \langle d, y - x \rangle$$

so Thm  $x \in C$  is a global minimizer iff

$\exists d \in \partial f(x)$  st.  $\forall y \in C, \langle d, y - x \rangle \geq 0$

"Euler inequality" (type of VI)

proof of Thm.

$\Leftarrow$  follows directly by definition of subgradient

$\Rightarrow$  ( for simplicity, we'll assume  $f$  is differentiable at  $x$ , so  $d = \nabla f(x)$  )

Suppose  $\exists y \in C$  st.  $\langle \nabla f(x), y - x \rangle < 0$

Let  $\varphi(t) := f(x + t \cdot (y - x))$  so

$$\varphi'(0) = \langle \nabla f(x), y - x \rangle \text{ via chain rule} \\ < 0 \text{ by assumption.}$$

But

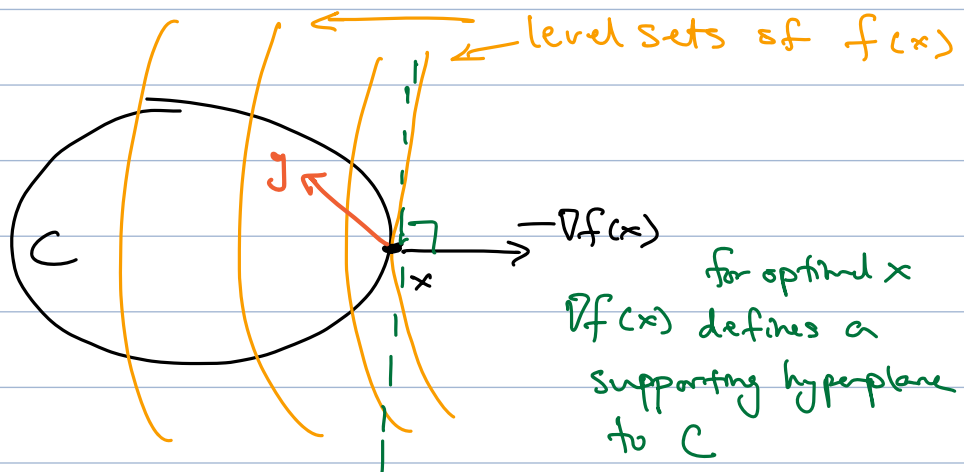
$$\varphi'(0) = \lim_{t \rightarrow 0^+} \frac{\varphi(t) - \varphi(0)}{t} < 0$$

$$\Rightarrow \exists t > 0 \text{ s.t. } \frac{\varphi(t) - \varphi(0)}{t} < 0$$

$$\Rightarrow \varphi(t) < \varphi(0)$$

$$\Rightarrow f(x) \text{ not globally optimal. } \square$$

Visualization



# Optional material: VARIATIONAL INEQUALITIES

ref: "Finite dim. var. ineq. and complementarity problems", Facchinei and Pang, '02

Def let  $C \subseteq \mathbb{R}^n$  be closed (often assumed to be convex) and  $F: C \rightarrow \mathbb{R}^n$  a continuous operator, then the corresponding variational inequality problem is

$$\text{Find } x \in C \text{ s.t. } \forall y \in C, \langle F(x), y - x \rangle \geq 0$$

This generalizes optimization

Recall the normal cone  $N_C(x) = \{d \in \mathbb{R}^n : \langle d, y - x \rangle \leq 0 \forall y \in C\}$   
then VI is looking for  $-F(x) \in N_C(x)$

i.e.

$$0 \in F(x) + N_C(x) \quad \text{so think of } F \text{ as the subgradient operator}$$

If  $C$  is a cone, the VI can

be reformulated as a "complementarity problem" (CP):

$$\text{Find } x \in C \text{ s.t. } x \perp F(x) \text{ and } F(x) \in C^*$$

$$(C^* = \{d : \langle d, x \rangle \geq 0 \forall x \in C\} \text{ is dual cone})$$

$$\text{ex: } C = C^* = \mathbb{R}_+^n$$

and  $F$  affine is the Linear Complementarity Problem LCP

$$\text{Find } x \geq 0, \underbrace{Ax + b}_{F(x)} \geq 0 \text{ s.t. } x \perp Ax + b$$

$$A \in \mathbb{R}^{n \times n}$$

$$\Rightarrow \forall i, x_i = 0 \text{ or } (F(x))_i = 0 \quad \text{"complementary"}$$

VI are a non-trivial generalization of optimization

(also, subtle differences: VI look for equivalents of "stationary pts", so if not convex, these aren't equivalent to global minimizers)

eg VI are the KKT equations of optimization problems

ex  $\min f(x) := \langle c, x \rangle + \frac{1}{2} \langle x, Qx \rangle$

s.t.  $x \geq 0$

Let  $Q \geq 0$  so it's convex

optimality conditions:

14  $\mathcal{L}(x, y) = f(x) + \langle x, y \rangle$   
 $\nwarrow$  dual variable

KKT:

$$0 = \nabla_x \mathcal{L}(x, y) = c + 2x + y, \text{ i.e., } y = -2x - c$$

$$x^T y = 0, \quad x \geq 0, \quad y \geq 0$$

and a generic LCP is solve

$$\boxed{\begin{array}{l} x \geq 0, Ax + b \geq 0 \\ x \perp Ax + b \end{array}}$$

$$\Leftrightarrow x \geq 0, \quad \underbrace{Ax+b}_{y} \geq 0, \\ x^T (\underbrace{Ax+b}_{y}) = 0 \quad A = -Q$$

... so it's a LCP

... but a general LCP

need not have  $A \geq 0$  or  $A \leq 0$ : A indefinite is ok,  
in fact, A need not even be symmetric!

Other ex. of VI include finding Nash Equilibria