

Definitions: Let  $f: \mathbb{R}^n \rightarrow \mathbb{R} \cup \{+\infty\}$  be an extended real-valued function that is not identically  $+\infty$ .

③ Let  $S \subseteq \mathbb{R}^n$  be a set. The indicator of  $S$  is

$$\mathbb{1}_S(x) = \begin{cases} 0 & \text{if } x \in S \\ +\infty & \text{otherwise} \end{cases}$$

e.g.

$$\begin{aligned} \inf_{x \in S} f(x) & \quad \Leftrightarrow \quad \inf_{x \in \mathbb{R}^n} \{ f(x) + \mathbb{1}_S(x) \} \\ \text{constrained} & \qquad \qquad \qquad \text{unconstrained} \end{aligned}$$

Proposition: Let  $f, S$  be as before.

①  $f$  is convex  $\Leftrightarrow$   $\text{epi}(f)$  is convex.

②  $S$  is convex  $\Leftrightarrow$   $\mathbb{1}_S(x)$  is convex

(Exercise)

Corollary (Jensen's inequality)

Let  $f$  be as before. Then,  $f$  is convex iff

$$\begin{aligned} \forall x_1, \dots, x_k \in \mathbb{R}^n \\ \alpha_1, \dots, \alpha_k \geq 0, \\ \sum_{j=1}^k \alpha_j = 1 \end{aligned} \quad f\left(\sum_{j=1}^k \alpha_j x_j\right) \leq \sum_{j=1}^k \alpha_j f(x_j)$$

Note. When  $k=2$ , this is just the definition of a convex function.

Proof:

$(\Leftarrow)$  Obvious

$(\Rightarrow)$  Suppose that  $f$  is convex. Note that

$$(x_j, f(x_j)) \in \text{epi}(f), \quad \forall j \quad \text{epi}(f) = \{(x, t) : f(x) \leq t\}$$

By the proposition,  $\text{epi}(f)$  is convex.

$$\Rightarrow \sum_{j=1}^k \alpha_j \underbrace{(x_j, f(x_j))}_{\in \text{epi}(f)} \in \text{epi}(f)$$

$$\Rightarrow \sum_{j=1}^k \alpha_j (\underbrace{x_j, f(x_j)}_{\in \text{epi}(f)}) \in \text{epi}(f)$$

$$\Rightarrow \left( \underbrace{\sum_{j=1}^k \alpha_j x_j}_x, \underbrace{\sum_{j=1}^k \alpha_j f(x_j)}_t \right) \in \text{epi}(f)$$

$$\Rightarrow f\left(\sum_{j=1}^k \alpha_j x_j\right) \leq \sum_{j=1}^k \alpha_j f(x_j)$$

## Operations preserving convexity

① (Non-negative combinations)

Let  $f_1, \dots, f_k$  be convex functions;  $\alpha_1, \dots, \alpha_k \geq 0$ . Then,

$$f = \sum_{j=1}^k \alpha_j f_j \text{ is convex}$$

Proof: Take any  $x_1, x_2 \in \mathbb{R}^n$ ;  $\alpha \in [0, 1]$ .

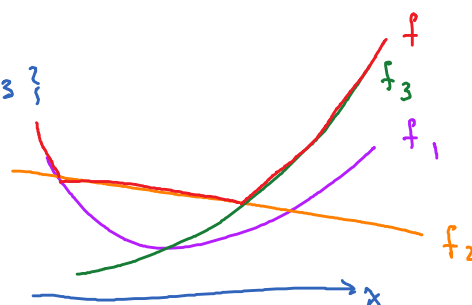
$$\begin{aligned} f(\alpha x_1 + (1-\alpha)x_2) &= \sum_{j=1}^k \alpha_j \underbrace{f_j(\alpha x_1 + (1-\alpha)x_2)}_{\geq 0 \leq \alpha f_j(x_1) + (1-\alpha)f_j(x_2)} \\ &\leq \sum_{j=1}^k \alpha_j [\alpha f_j(x_1) + (1-\alpha)f_j(x_2)] \\ &= \alpha f(x_1) + (1-\alpha)f(x_2). \end{aligned}$$

② (Pointwise supremum)

Let  $I$  be index set and  $\{f_i\}_{i \in I}$  be a family of convex functions. Then,

$$f = \sup_{i \in I} f_i \text{ is convex}$$

e.g.  $I = \{1, 2, 3\}$



e.g. Let  $\sigma: \mathbb{R}^{m \times n} \rightarrow \mathbb{R}_+$  be defined as

$$\begin{aligned}\sigma(X) &= \text{largest singular value of } X \\ &= \sqrt{\text{largest eigenvalue of } \underbrace{XX^T}_{\text{psd}}}\end{aligned}$$

Claim:  $\sigma(\cdot)$  is convex

Proof: By the Courant-Fischer theorem,

$$\sigma(X) = \max_{\substack{\|u\|_2=1 \\ \|v\|_2=1}} u^T X v$$

Let  $\underbrace{f_{u,v}}_{\text{index}}(X) = u^T X v$ ,  $I = \{(u, v) : \|u\|_2=1, \|v\|_2=1\}$ .

Then,  $\sigma(X) = \sup_{(u,v) \in I} f_{u,v}(X)$ .

Observe that  $X \mapsto f_{u,v}(X)$  is linear hence convex

$$\hookrightarrow f_{u,v}(\alpha X + \beta Y) = \alpha f_{u,v}(X) + \beta f_{u,v}(Y)$$

### ③ (Composition with increasing convex function)

Let  $g: \mathbb{R}^n \rightarrow \mathbb{R}$  be convex,  $h: \mathbb{R} \rightarrow \mathbb{R}$  be convex. Then,

$f = h \circ g$  (i.e.,  $f(x) = h(g(x))$ ) is not necessarily convex

e.g.  $g(x) = x^2$ ,  $h(x) = -x \Rightarrow f(x) = -x^2$

However, if we assume in addition that  $h$  is increasing, then  $f = h \circ g$  is convex.

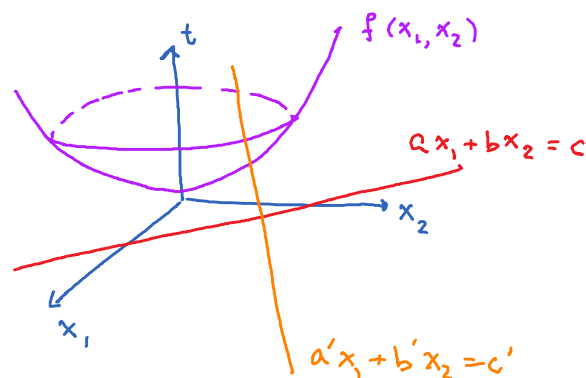
### ④ (Restriction on Lines)

Definition: Given a point  $x_0 \in \mathbb{R}^n$ ,

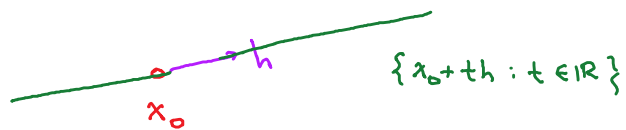
a direction  $h \in \mathbb{R}^n \setminus \{0\}$ , we call

the set  $\{x_0 + th : t \in \mathbb{R}\}$  a line

$\downarrow$  ...



through  $x_0$  in the direction  $h$ .



Let  $f: \mathbb{R}^n \rightarrow \mathbb{R}$  be a function and define

$$\mathbb{R} \ni t \mapsto \underbrace{\tilde{f}_{x_0, h}(t)}_{\text{single-variable}} = \underbrace{f(x_0 + th)}_{\in \mathbb{R}^n}$$

to be the restriction of  $f$  on the line  $\{x_0 + th : t \in \mathbb{R}\}$ .

Then,

$$f \text{ is convex} \Leftrightarrow \forall x_0, h, \tilde{f}_{x_0, h} \text{ is convex}$$