

$f: \mathbb{R}^n \rightarrow \mathbb{R}$, $D \subseteq \mathbb{R}^n$ convesso

(f convessa $\stackrel{\text{def}}{\iff} (-f)$ convessa) ①

$x, y \in D, \lambda \in [0, 1] \implies f(\lambda x + (1-\lambda)y) \leq \lambda f(x) + (1-\lambda)f(y)$

OPERAZIONI SULLE FUNZIONI CONVESSE

• SOMMA: f_i convesse, $i \in I, |I| < +\infty \implies f(x) = \sum_{i \in I} f_i(x)$ convessa

• MOLT. SCALARE: f convessa, $\mu \geq 0 \implies (\mu f)(x) = \mu f(x)$ è convessa

• COMPOSIZIONE

Affine $A \in \mathbb{R}^{n \times m}, b \in \mathbb{R}^m, f$ convessa $\implies x \mapsto f(Ax+b)$ convessa

Convessa $h: \mathbb{R} \rightarrow \mathbb{R}$

- f convessa, h convessa non decrescente } $\implies (h \circ f)(x) = h(f(x))$ convessa
 - f convessa, h convessa non crescente }

(possibile considerare anche composizione tra fz. vettoriali e comp. convesse)

• ESTREMO SUPERIORE PUNTUALE

f_i convesse, $i \in I \implies (\sup_{i \in I} f_i)(x) = \sup_{i \in I} f_i(x)$ convessa \nearrow (dim. attraverso epi)

Nota: $\infty |I| = +\infty$ può darsi che $\sup_{i \in I} f_i(x) = +\infty$ per qualche x (\rightarrow fz. convesse $\mathbb{R}^n \rightarrow \mathbb{R} \cup \{+\infty\}$)
 necessita di introdurre dominio

fz. poliedrali convesse \equiv sup # finito di fz. affini

dominio $\{x \mid f(x) < +\infty\}$

PROPRIETA' E CARATTERIZZAZIONI

• Epigrafico: $(\text{epi } f) \cap [D \times \mathbb{R}] = \{(x, t) \in D \times \mathbb{R} \mid t \geq f(x)\}$
 convesso $\iff f$ convessa su D

• Sottolivelli: f convessa su $D \implies \{x \in \mathbb{R}^n : f(x) \leq \alpha\} \cap D$ convesso
 (quasiconvessità) $\iff \forall \alpha \in \mathbb{R} S_f(\alpha)$

FZ CONVESSE "SMOOTH"

• Caratterizzazione "piano tangente al grafico"

• Caratterizzazioni del secondo ordine

• monotonia del gradiente

Prop Sia f differenziabile su D . Allora

- i) f convessa su $D \iff (\nabla f(y) - \nabla f(x))^T (y - x) \geq 0 \quad \forall x, y \in D$
- ii) f strettamente convessa su $D \iff (\nabla f(y) - \nabla f(x))^T (y - x) > 0 \quad \forall x, y \in D, x \neq y$
- iii) f fortemente convessa su D di modulo $\mu \iff (\nabla f(y) - \nabla f(x))^T (y - x) \geq \mu \|y - x\|^2 \quad \forall x, y \in D$

dim i) \implies la convessità garantisce

$$f(y) \geq f(x) + \langle \nabla f(x), y - x \rangle$$

$$f(x) \geq f(y) + \langle \nabla f(y), x - y \rangle$$

la tesi segue sommando membro a membro

\Leftarrow) Sia $g(t) = f(x + t(y - x))$, $x, y \in D$

f differenziabile $\implies g$ derivabile e $g'(t) = \nabla f(x + t(y - x))^T (y - x)$

L'ipotesi può essere riscritta come $g'(t) \geq g'(0) \quad \forall t \in [0, 1]$

$$f(y) = g(1) = g(0) + \int_0^1 g'(t) dt \geq g(0) + g'(0) = f(x) + \nabla f(x)^T (y - x)$$

Dall'arbitrarietà di x e y segue la convessità di f su D .

ii) envelope

iii) Applicare i) a $f(x) - \mu/2 \|x\|^2$

CONTINUITÀ (LIPSCHITZIANA) delle FZ. CONVESSE (Roberts-Varberg, The American Math. Monthly, 81 (1974) 1014-1016)

Teo Sia $D \subseteq \mathbb{R}^n$ convesso con $\text{int } D \neq \emptyset$ e f convessa su D . Allora

- i) f è localmente lipschitziana vicino ad ogni $\bar{x} \in \text{int } D$
- [ii) f è globalmente lipschitziana su ogni $D' \subseteq D$ compatto]

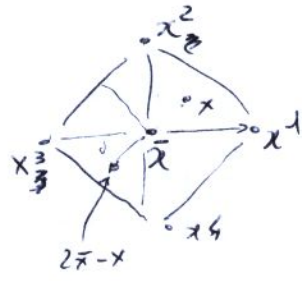
Cor f convessa su $D \implies f$ continua in ogni $x \in \text{int } D$ (Nota: f può essere discontinua su ∂D)

Per dimostrare il teorema, si usa il seguente

(3)

Lemma f convessa su $D \Rightarrow f$ limitata in un intorno di ogni $\bar{x} \in \text{int } D$

dim $x^i = \bar{x} + \delta e_i$ $\left\{ \begin{array}{l} \text{con } \delta > 0 \text{ t.c. } x^i \in D \\ i = 1, \dots, n \end{array} \right.$
 $x^{n+i} = \bar{x} - \delta e_i$



$$T = \left\{ \sum_{i=1}^{2n} \lambda_i x^i \mid \lambda_i \geq 0, \sum_{i=1}^{2n} \lambda_i = 1 \right\}$$

$$x \in T, \text{ int } T \neq \emptyset \quad (B(x, \sqrt{2}/2 \delta) \subseteq T)$$

$$\hookrightarrow x = \sum_{i=1}^{2n} \lambda_i x^i \Rightarrow f(x) \leq \sum_{i=1}^{2n} \lambda_i f(x^i) \leq \max_{i=1, \dots, 2n} f(x^i) =: M$$

~~...~~

$$\bar{x} = x_{/2} + (2\bar{x} - x)_{/2} \quad \hat{x} = 2\bar{x} - x \rightarrow \hat{x} \in T$$

$$f(\bar{x}) \leq \frac{1}{2} f(x) + \frac{1}{2} f(\hat{x}) \rightarrow f(x) \geq 2f(\bar{x}) - f(\hat{x}) \geq 2f(\bar{x}) - M$$

Quindi f è limitata su T

dim teo 1) Grazie al lemma, esistono $M = M(\bar{x}), \varepsilon = \varepsilon(\bar{x}) > 0$ t.c.

$$|f(x)| \leq M \quad \forall x \in B(\bar{x}, 2\varepsilon)$$

Siano $x, y \in B(\bar{x}, \varepsilon)$ con $x \neq y$, e si ponga $\alpha = \|x - y\|$. Allora

$$z = x + \frac{\varepsilon}{\alpha} (y - x) \in B(\bar{x}, 2\varepsilon)$$

$$\frac{\alpha + \varepsilon}{\alpha} x - \frac{\varepsilon}{\alpha} y \quad \text{da cui} \quad x = \frac{\alpha}{\alpha + \varepsilon} z + \frac{\varepsilon}{\alpha + \varepsilon} y$$

$$e \quad f(x) \leq \frac{\alpha}{\alpha + \varepsilon} f(z) + \frac{\varepsilon}{\alpha + \varepsilon} f(y) \quad \text{Sottraendo } f(y) \text{ ad ambo membri:}$$

$$f(x) - f(y) \leq \frac{\alpha}{\alpha + \varepsilon} [f(z) - f(y)] \leq \frac{\alpha}{\varepsilon} |f(z) - f(y)| \leq \frac{2M}{\varepsilon} \alpha = \frac{2M}{\varepsilon} \|x - y\|$$

Invertendo i ruoli di x e y si ottiene anche $f(y) - f(x) \leq \frac{2M}{\varepsilon} \|x - y\|$, e quindi

$$|f(x) - f(y)| \leq \frac{2M}{\varepsilon} \|x - y\| \quad \forall x, y \in B(\bar{x}, \varepsilon)$$

Oss $f: \mathbb{R}^n \rightarrow \mathbb{R}$ convessa su $\mathbb{R}^n \Rightarrow \text{epi } f, S_f(\alpha)$ sono chiusi ($\alpha \in \mathbb{R}$) (4)

Nota Anche in assenza di convessità vale:

f inf.nte semicontinua $\Leftrightarrow \text{epi } f$ chiuso $\Leftrightarrow S_f(\alpha)$ chiuso $\forall \alpha \in \mathbb{R}$
(le f inf.nte semicontinue vengono anche chiamate chiuse)

ESISTENZA DERIVATA DIREZIONALE

$$f'(\bar{x}; d) = \lim_{t \downarrow 0} [f(\bar{x} + td) - f(\bar{x})]/t \quad (\text{se } \exists \text{ lim})$$

Prop Una fz. convessa su $D \subseteq \mathbb{R}^n$ ammette derivata direzionale $f'(\bar{x}; d)$ in ogni direzione $d \in \mathbb{R}^n$ in ogni punto $\bar{x} \in \text{int } D$.

dim Sia $g(t) = [f(\bar{x} + td) - f(\bar{x})]/t$ (se t suff.nte piccolo $\bar{x} + td \in D$)

f loc.nte lips. $\Rightarrow \|g(t)\| = \| [f(\bar{x} + td) - f(\bar{x})]/t \| \leq M \|d\|$ se t suff.nte piccolo ($t > 0$)

Siano $0 < t_2 < t_1$ t.c. $\bar{x} + t_1 d \in D$:

$$\bar{x} + t_2 d = (1 - t_2/t_1) \bar{x} + t_2/t_1 (\bar{x} + t_1 d)$$

$$f(\bar{x} + t_2 d) \leq (1 - t_2/t_1) f(\bar{x}) + t_2/t_1 f(\bar{x} + t_1 d)$$

$$f(\bar{x} + t_2 d) - f(\bar{x}) \leq \frac{t_2}{t_1} [f(\bar{x} + t_1 d) - f(\bar{x})] \rightarrow g(t_2) \leq g(t_1)$$

g limitata e decrescente su $[0, t_1] \Rightarrow \exists f'(\bar{x}; d) = \lim_{t \downarrow 0} g(t) = \inf_{t > 0} g(t)$ ■

SOTTOGRADIENTI E SOTTODIFFERENZIALE

↳ Nota:
 $|f'(\bar{x}; d)| \leq M \|d\|$

~~Def~~ $f: \mathbb{R}^n \rightarrow \mathbb{R}$ convessa su $D \subseteq \mathbb{R}^n$ (D convesso)

Def $s \in \mathbb{R}^n$ si dice SOTTOGRADIENTE di f in $\bar{x} \in D$ se
 $f(x) \geq f(\bar{x}) + \langle s, x - \bar{x} \rangle \quad \forall x \in D$

Def $\partial f(\bar{x}) = \{ s \in \mathbb{R}^n \mid s \text{ è sottogradiente di } f \text{ in } \bar{x} \}$ si dice
SOTTODIFFERENZIALE di f in $\bar{x} \in D$

Prop Sia f differenziabile in $\bar{x} \in \text{int} D$. Allora $\partial f(\bar{x}) = \{ \nabla f(\bar{x}) \}$ (5)

dim Siano $s \in \partial f(\bar{x})$, $d = s - \nabla f(\bar{x})$ e $t > 0$ t.c. $\bar{x} + td \in D$.

$$s \in \partial f(\bar{x}) \Rightarrow f(\bar{x} + td) \geq f(\bar{x}) + t \langle s, d \rangle$$

$$f \text{ diff.} \Rightarrow f(\bar{x} + td) = f(\bar{x}) + t \langle \nabla f(\bar{x}), d \rangle + r(td)$$

$$\text{da cui } 0 \geq t \langle s - \nabla f(\bar{x}), d \rangle + r(td) \text{ e } 0 \geq \langle s - \nabla f(\bar{x}), d \rangle + r(td)/t$$

Considerando $t \downarrow 0$ si ottiene $0 \geq \langle s - \nabla f(\bar{x}), d \rangle = \|s - \nabla f(\bar{x})\|^2$
 ovvero $s = \nabla f(\bar{x})$

Teo $\partial f(\bar{x})$ è non vuoto, convesso e compatto per ogni $\bar{x} \in \text{int} D$.

dim $s_1, s_2 \in \partial f(\bar{x})$, $\lambda \in [0, 1]$

$$f(\bar{x}) + \langle \lambda s_1 + (1-\lambda)s_2, x - \bar{x} \rangle = \lambda [f(\bar{x}) + \langle s_1, x - \bar{x} \rangle] + (1-\lambda) [f(\bar{x}) + \langle s_2, x - \bar{x} \rangle] \leq \lambda f(x) + (1-\lambda)f(x) = f(x)$$

CONTINUITA'

$\partial f(\bar{x})$ è chiuso per la continuità di $s \mapsto \langle s, x - \bar{x} \rangle$

$\partial f(\bar{x})$ è limitato poiché f è localmente lipschitziana vicino a \bar{x} :

$$\langle s, x - \bar{x} \rangle \leq f(x) - f(\bar{x}) \leq L \|x - \bar{x}\| \text{ se } x \in B(\bar{x}, \varepsilon) \text{ per } \varepsilon > 0 \text{ opportuno}$$

$$x = \bar{x} + \frac{\varepsilon}{\|s\|} s : \frac{\varepsilon}{\|s\|} \langle s, s \rangle \leq \frac{\varepsilon L \|s\|}{\|s\|} \rightarrow \|s\| \leq L$$

$\partial f(\bar{x}) \neq \emptyset$ richiede il seguente corollario del teorema di separazione stretta:

Cor $A \subseteq \mathbb{R}^m$ convesso, $\bar{z} \in \partial A \Rightarrow \exists z^* \in \mathbb{R}^m, z^* \neq 0$ t.c. $\langle z^*, z \rangle \leq \langle z^*, \bar{z} \rangle \forall z \in A$.

$(\bar{x}, f(\bar{x})) \in \partial(\text{epi } f)$, quindi $\exists (s^*, u^*) \in \mathbb{R}^n \times \mathbb{R}$ $(s^*, u^*) \neq (0, 0)$ t.c.

$$\langle s^*, x \rangle + u^* t \leq \langle s^*, \bar{x} \rangle + u^* f(\bar{x}) \quad \forall x \in D \quad \forall t \geq f(x)$$

$$\langle s^*, x - \bar{x} \rangle + u^* (t - f(\bar{x})) \leq 0 \quad (*)$$

$u^* \leq 0$, altrimenti $t \uparrow$ va contraddice (*).

Se fosse $u^* = 0$, risulterebbe $\langle s^*, x - \bar{x} \rangle \leq 0 \quad \forall x \in D$ e quindi $s^* = 0$ poiché $\bar{x} \in \text{int} D$

Quindi $u^* < 0$ e possiamo supporre $u^* = -1$: $\langle s^*, x - \bar{x} \rangle + f(\bar{x}) - t \leq 0$

da cui per $t=f(x)$ si ottiene $f(x) \geq f(\bar{x}) + \langle s^*, x - \bar{x} \rangle$, ovvero $s^* \in \partial f(\bar{x})$ ⑥

Prop Siano f strettamente convessa su D e $s^* \in \partial f(\bar{x})$ per $\bar{x} \in \text{int} D$. Allora

$$f(x) > f(\bar{x}) + \langle s^*, x - \bar{x} \rangle \quad \forall x \in D, x \neq \bar{x}.$$

dim Per def. $f(x) \geq f(\bar{x}) + \langle s^*, x - \bar{x} \rangle \quad \forall x \in D$ \square

Supponiamo esista $\hat{x} \in D$ t.c. $f(\hat{x}) = f(\bar{x}) + \langle s^*, \hat{x} - \bar{x} \rangle$. Sia $\lambda \in]0, 1[$:

$$f(\lambda \hat{x} + (1-\lambda)\bar{x}) < \lambda f(\hat{x}) + (1-\lambda)f(\bar{x}) = f(\bar{x}) + \lambda \langle s^*, \hat{x} - \bar{x} \rangle$$

in contraddizione con \square per $x = \lambda \hat{x} + (1-\lambda)\bar{x}$. \blacksquare

Analogamente al caso differenziabile si dimostra:

Prop Se per ogni $\bar{x} \in \text{int} D$, $\partial f(\bar{x}) \neq \emptyset$, allora f è convessa su $\text{int} D$.

Per semplicità d'ora in avanti, supponiamo $f: \mathbb{R}^n \rightarrow \mathbb{R}$ convessa su \mathbb{R}^n

Prop $\partial f(\bar{x}) = \{ s \in \mathbb{R}^n \mid f'(\bar{x}; d) \geq \langle s, d \rangle \quad \forall d \in \mathbb{R}^n \}$

dim \subseteq) $s \in \partial f(\bar{x}) \rightarrow f(\bar{x} + td) \geq f(\bar{x}) + t \langle s, d \rangle \rightarrow \frac{f(\bar{x} + td) - f(\bar{x})}{t} \geq \langle s, d \rangle$
 $t \downarrow 0 \rightarrow f'(\bar{x}; d) \geq \langle s, d \rangle$

\supseteq) Sia $s \in \mathbb{R}^n$ t.c. $f'(\bar{x}; d) \geq \langle s, d \rangle \quad \forall d \in \mathbb{R}^n$.

$$\langle s, d \rangle \leq f'(\bar{x}; d) = \inf_{t>0} \frac{f(\bar{x} + td) - f(\bar{x})}{t} \leq \frac{f(\bar{x} + d) - f(\bar{x})}{1}$$

da cui ~~con~~ con $d = y - \bar{x}$: $f(y) \geq f(\bar{x}) + \langle s, y - \bar{x} \rangle \quad \forall y \in \mathbb{R}^n$
 ovvero $s \in \partial f(\bar{x})$ \square

Lemma $d \mapsto f'(\bar{x}; d)$ è sublineare per ogni $\bar{x} \in \mathbb{R}^n$

dim Sia $\gamma > 0$: $f'(\bar{x}; \gamma d) = \lim_{t \downarrow 0} \gamma \frac{f(\bar{x} + \gamma t d) - f(\bar{x})}{\gamma t} = \gamma \lim_{t \downarrow 0} \frac{f(\bar{x} + t d) - f(\bar{x})}{t}$

Siano $d_1, d_2 \in \mathbb{R}^n$:

$$\bar{x} + t(d_1 + d_2) = \frac{1}{2}(\bar{x} + 2td_1) + \frac{1}{2}(\bar{x} + 2td_2)$$

$\gamma f'(\bar{x}; d)$

$$f(\bar{x} + t(d_1 + d_2)) \leq \frac{1}{2} f(\bar{x} + 2td_1) + \frac{1}{2} f(\bar{x} + 2td_2) \quad \text{da cui}$$

$$\frac{f(\bar{x} + t(d_1 + d_2)) - f(\bar{x})}{t} \leq \frac{f(\bar{x} + 2td_1) - f(\bar{x})}{2t} + \frac{f(\bar{x} + 2td_2) - f(\bar{x})}{2t} \quad \text{da cui t > 0:}$$

$$f'(\bar{x}; d_1 + d_2) \leq f'(\bar{x}; d_1) + f'(\bar{x}; d_2)$$

Teo $f'(\bar{x}, \cdot)$ è la funzione di supporto di $\partial f(\bar{x})$ per ogni $\bar{x} \in \mathbb{R}^n$, ovvero

$$f'(\bar{x}; d) = \max \{ \langle s, d \rangle \mid s \in \partial f(\bar{x}) \} \quad \forall d \in \mathbb{R}^n$$

dim Siano $s \in \partial f(\bar{x})$, $d \in \mathbb{R}^n$

$$f'(\bar{x}; d) = \inf_{t > 0} \frac{f(\bar{x} + td) - f(\bar{x})}{t} \geq \inf_{t > 0} \frac{t \langle s, d \rangle}{t} = \langle s, d \rangle$$

Dall'arbitrarietà di s segue $f'(\bar{x}; d) \geq \max \{ \langle s, d \rangle \mid s \in \partial f(\bar{x}) \}$.

Supponiamo che esista $\bar{d} \in \mathbb{R}^n$ t.c.

$$f'(\bar{x}; \bar{d}) > \max \{ \langle s, \bar{d} \rangle \mid s \in \partial f(\bar{x}) \} = \langle \bar{s}, \bar{d} \rangle$$

per l'opportuno $\bar{s} \in \partial f(\bar{x})$. Senza perdere di generalità possiamo supporre $\|\bar{d}\| = 1$

Siano $\gamma = f'(\bar{x}; \bar{d}) - \langle \bar{s}, \bar{d} \rangle > 0$ e $\hat{s} = \bar{s} + \gamma \bar{d}$ (per la positività omogeneità di $f(\bar{x}; \cdot)$ e $\langle s, \cdot \rangle$)

$$\langle \hat{s}, \bar{d} \rangle = \langle \bar{s}, \bar{d} \rangle + \gamma \langle \bar{d}, \bar{d} \rangle = \langle \bar{s}, \bar{d} \rangle + \gamma = f'(\bar{x}; \bar{d})$$

$$\langle \hat{s}, -\bar{d} \rangle = -\langle \hat{s}, \bar{d} \rangle = -f'(\bar{x}; \bar{d}) \leq f'(\bar{x}; -\bar{d})$$

$$(0 = f'(\bar{x}; 0) = f'(\bar{x}; \bar{d} - \bar{d}) \leq f'(\bar{x}; \bar{d}) + f'(\bar{x}; -\bar{d}))$$

Quindi $\langle \hat{s}, \gamma \bar{d} \rangle \leq f'(\bar{x}; \gamma \bar{d}) \quad \forall \gamma \in \mathbb{R}$

Dal teo (Hahn-Banach) segue che esiste $s \in \mathbb{R}^n$ t.c. $\left\{ \begin{array}{l} \langle s, \bar{d} \rangle = \langle \hat{s}, \bar{d} \rangle \\ f'(\bar{x}; d) \geq \langle s, d \rangle \quad \forall d \in \mathbb{R}^n \end{array} \right.$

Quindi $s \in \partial f(\bar{x})$, ma $\langle s, \bar{d} \rangle = \langle \hat{s}, \bar{d} \rangle > \langle \bar{s}, \bar{d} \rangle$

in contraddizione con la scelta di \bar{s}

Prop Siano $t > 0$, $f_i: \mathbb{R}^n \rightarrow \mathbb{R}$ convessa su \mathbb{R}^n $i=1,2$. Allora per ogni $\bar{x} \in \mathbb{R}^n$ (8)

valgono: i) $\partial(t f_1)(\bar{x}) = t \partial f_1(\bar{x})$

ii) $\partial(f_1 + f_2)(\bar{x}) = \partial f_1(\bar{x}) + \partial f_2(\bar{x})$

dim i) Immediata conseguenza della definizione o equivalentemente della positiva omogeneità di $f'(\bar{x}; \cdot)$.

ii) I due insiemi hanno la stessa funzione di supporto:

$$\begin{aligned} \sigma_{\partial(f_1+f_2)(\bar{x})}(d) &= \max \{ \langle s, d \rangle \mid s \in \partial(f_1+f_2)(\bar{x}) \} = (f_1+f_2)'(\bar{x}; d) = \\ &= f_1'(\bar{x}; d) + f_2'(\bar{x}; d) = \max \{ \langle s, d \rangle \mid s \in \partial f_1(\bar{x}) \} + \max \{ \langle s, d \rangle \mid s \in \partial f_2(\bar{x}) \} \\ &= \max \{ \langle s, d \rangle \mid s \in \partial f_1(\bar{x}) + \partial f_2(\bar{x}) \} = \sigma_{\partial f_1(\bar{x}) + \partial f_2(\bar{x})}(d) \quad \forall d \in \mathbb{R}^n. \end{aligned}$$

$\partial f_i(\bar{x})$ compatto, convesso $\Rightarrow \partial f_1(\bar{x}) + \partial f_2(\bar{x})$ compatto, convesso.

Due insiemi convessi e compatti, hanno la stessa funzione di supporto se e solo se sono uguali*, pertanto $\partial(f_1+f_2)(\bar{x}) = \partial f_1(\bar{x}) + \partial f_2(\bar{x})$ □

* Prop Siano $A, B \subseteq \mathbb{R}^n$ convessi e ~~compatti~~ ^{chiusi}. Allora

$$\max \{ \langle s, d \rangle \mid s \in A \} \leq \max \{ \langle s, d \rangle \mid s \in B \} \quad \forall d \in \mathbb{R}^n \Leftrightarrow A \subseteq B$$

$\overset{\sigma_A(d)}{\parallel} \qquad \qquad \qquad \overset{\sigma_B(d)}{\parallel}$

dim \Leftarrow) ovvio

\Rightarrow) Supponiamo che esista $\bar{s} \in A$ t.c. $\bar{s} \notin B$. Per il teo (separazione stretto) esistono $\bar{d} \in \mathbb{R}^n$, $\gamma \in \mathbb{R}$ tali che

$$\langle \bar{s}, \bar{d} \rangle \geq \gamma > \langle s, \bar{d} \rangle \quad \forall s \in B$$

da cui la contraddizione

$$\sigma_A(\bar{d}) \geq \langle \bar{s}, \bar{d} \rangle > \gamma \geq \max \{ \langle s, \bar{d} \rangle \mid s \in B \} = \sigma_B(\bar{d}).$$

~~Allo stesso modo si vede che~~ □

Prop** Siano $S_1, \dots, S_K \subseteq \mathbb{R}^n$ convessi e compatti e sia $S = \bigcup_{i=1}^K S_i$. Allora (9)

$$\max_{i=1, \dots, K} \sigma_{S_i}(d) = \sigma_{\text{conv} S}(d) \quad \forall d \in \mathbb{R}^n \quad \rightarrow \text{(nota: } S \text{ è compatto)}$$

dove $\text{conv} S = \left\{ \sum_{i=1}^{n+1} \lambda_i s^i \mid s^i \in S, \lambda_i \geq 0, \sum_{i=1}^{n+1} \lambda_i = 1 \right\}$.

dim $S_i \subseteq \text{conv} S \Rightarrow \sigma_{S_i}(d) = \max \{ \langle s, d \rangle \mid s \in S_i \} \leq \max \{ \langle s, d \rangle \mid s \in \text{conv} S \} = \sigma_{\text{conv} S}(d)$

$s \in \text{conv} S \Rightarrow s = \sum_{i=1}^{n+1} \lambda_i s^i : \langle s, d \rangle = \sum_{i=1}^{n+1} \lambda_i \langle s^i, d \rangle \leq \left(\sum_{i=1}^{n+1} \lambda_i \right) \max_{i=1, \dots, n+1} \langle s^i, d \rangle =$
 $= \max_i \langle s^i, d \rangle \leq \sigma_{S_{\bar{i}}}(d) \leq \max_i \sigma_{S_i}(d)$ dove \bar{i} t.c. $\max \langle s^i, d \rangle = \langle s^{\bar{i}}, d \rangle$
 $\text{e } s^{\bar{i}} \in S_{\bar{i}}.$ ■

Prop Siano $f_i: \mathbb{R}^n \rightarrow \mathbb{R}$ convessa su \mathbb{R}^n $(i=1, \dots, m)$ e $f(x) = \max \{ f_1(x), f_2(x), \dots, f_m(x) \}$.

Allora per ogni $\bar{x} \in \mathbb{R}^n$ risulta

$$\partial f(\bar{x}) = \text{conv} \left\{ \bigcup_{i \in I_f(\bar{x})} \partial f_i(\bar{x}) \right\} \quad \text{dove } I_f(\bar{x}) = \{ i \mid f(\bar{x}) = f_i(\bar{x}) \}$$

dim Siano $s \in \partial f_i(\bar{x})$ con $i \in I_f(\bar{x})$ e $y \in \mathbb{R}^n$:

$$f(y) \geq f_i(y) \geq f_i(\bar{x}) + \langle s, y - \bar{x} \rangle = f(\bar{x}) + \langle s, y - \bar{x} \rangle$$

da cui $s \in \partial f(\bar{x})$. Poiché $\partial f(\bar{x})$ è convesso e $\partial f_i(\bar{x}) \subseteq \partial f(\bar{x})$ per $i \in I_f(\bar{x})$, segue che $\text{conv} \left\{ \bigcup_{i \in I_f(\bar{x})} \partial f_i(\bar{x}) \right\} \subseteq \partial f(\bar{x})$.

Per le due precedenti proposizioni l'inclusione opposta vale se

$$f'(\bar{x}; d) \leq \max \{ f'_i(\bar{x}; d) \mid i \in I_f(\bar{x}) \} \quad \forall d \in \mathbb{R}^n.$$

Siano $d \in \mathbb{R}^n$ e $t_k \downarrow 0$: sia $I_k = I_f(\bar{x} + t_k d)$; per costruzione $I_k \neq \emptyset$ per ogni k e la continuità delle f_i garantisce che $I_k \subseteq I_f(\bar{x})$ se k è sufficientemente grande.

Per la finitarietà del numero di f_i esistono $j \in I_f(\bar{x})$ e una sottosuccessione k_e t.c.

$j \in I_{k_e}$ per ogni e . Quindi:

$$f'(\bar{x}; d) = \lim_{e \rightarrow +\infty} \frac{[f(\bar{x} + t_{k_e} d) - f(\bar{x})]}{t_{k_e}} = \lim_{e \rightarrow +\infty} \frac{[f_j(\bar{x} + t_{k_e} d) - f_j(\bar{x})]}{t_{k_e}} = f'_j(\bar{x}; d) \leq$$

$$\leq \max \{ f'_i(\bar{x}; d) \mid i \in I_f(\bar{x}) \}$$

Cor Se f_i sono inoltre differenziabili in \bar{x} , allora $\partial f(\bar{x}) = \text{conv} \{ \nabla f_i(\bar{x}) \mid i \in I_f(\bar{x}) \}$.

Prop Sia $f: \mathbb{R}^n \rightarrow \mathbb{R}$ convessa su \mathbb{R}^n . Allora per ogni $\bar{x} \in \mathbb{R}^n$ risulta

$$\partial f(\bar{x}) = \left\{ s \in \mathbb{R}^n \mid (s, -1) \in N(\text{epi } f, (\bar{x}, f(\bar{x}))) \right\}$$

dim $(s, -1) \in N(\text{epi } f, (\bar{x}, f(\bar{x}))) \Leftrightarrow \forall y \in \mathbb{R}^n \forall r \geq f(y) : \langle s, y - \bar{x} \rangle + (-1)(r - f(\bar{x})) \leq 0$

$$\Leftrightarrow \forall y \in \mathbb{R}^n \forall r \geq f(y) : \langle s, y - \bar{x} \rangle + f(\bar{x}) \leq r$$

\Rightarrow
si prende
 $r = f(y)$

$$\Leftrightarrow s \in \partial f(\bar{x})$$

■

TEOREMI DI SEPARAZIONE

(A)

Mangasarian, Nonlinear programming, SIAM 1994 (McGraw-Hill 1969)

Chp 3 (richiede Chp 2 [teoremi di alternative])

Bazaraa - Sherali - Shetty, Nonlinear programming: theory & algorithms, Wiley 1993

Section 2.4

Teo (separazione stretta)

$A \subseteq \mathbb{R}^m$ convesso, chiuso, $B \subseteq \mathbb{R}^m$ compatto.

$A \cap B = \emptyset \Rightarrow \exists z^* \in \mathbb{R}^m, \gamma \in \mathbb{R}$ t.c. $\langle z^*, z \rangle < \gamma < \langle z^*, w \rangle$ $\forall z \in A$
 $\forall w \in B$

Cor $A \subseteq \mathbb{R}^m$ convesso, $\bar{z} \in \partial A \Rightarrow \exists z^* \in \mathbb{R}^m, z^* \neq 0$ t.c. $\langle z^*, z - \bar{z} \rangle \leq 0 \forall z \in A$

dim $\bar{z} \in \partial A \Rightarrow \exists z_k \rightarrow \bar{z}$ con $z_k \notin \text{cl} A$

Si applica il teo (separazione stretta) ~~con~~ per $\text{cl} A$ e $\{z_k\}$ e si normalizza z_k^* e si passa al limite $k \rightarrow +\infty$.

Esempi di fz. convesse

(B)

1) $x \mapsto \|x\|$ [non differenziabile in $\bar{x} = 0$]

2) $x \mapsto \|x\|^2$ [differenziabile]

la convessità segue immediatamente dall'uguaglianza

$$\|\lambda x + (1-\lambda)y\|^2 = \lambda \|x\|^2 + (1-\lambda)\|y\|^2 - \lambda(1-\lambda)\|x-y\|^2$$

$$\begin{aligned} & (\lambda \langle x, x \rangle + (1-\lambda)\langle y, y \rangle - \lambda(1-\lambda)\langle x-y, x-y \rangle = \\ & = \lambda \langle x, x \rangle + (1-\lambda)\langle y, y \rangle - \lambda(1-\lambda)[\langle x, x \rangle + \langle y, y \rangle - 2\langle x, y \rangle] = \\ & = \lambda^2 \langle x, x \rangle + (1-\lambda)^2 \langle y, y \rangle + 2\lambda(1-\lambda)\langle x, y \rangle = \|\lambda x + (1-\lambda)y\|^2) \end{aligned}$$

3) $x \mapsto \frac{1}{2} x^T Q x + b^T x$ con $Q \in \mathbb{R}^{n \times n}$, $Q = Q^T$ semidefinita positiva

4) $x \mapsto \inf \{ \|x-y\|^2 : y \in C \}$ con C convesso

Nota $y \mapsto \|x-y\|^2$ è fortemente convessa, quindi $\inf = \min > -\infty$.

Siano $\varepsilon > 0$, $y_1, y_2 \in C$ t.c. $\|x_i - y_i\|^2 \leq f(x_i) + \varepsilon$ $i=1,2$, $\lambda \in [0,1]$

$$\begin{aligned} f(\lambda x_1 + (1-\lambda)x_2) & \leq \|\lambda x_1 + (1-\lambda)x_2 - \lambda y_1 - (1-\lambda)y_2\|^2 = \\ & = \|\lambda(x_1 - y_1) + (1-\lambda)(x_2 - y_2)\|^2 \leq \\ & \leq \lambda \|x_1 - y_1\|^2 + (1-\lambda)\|x_2 - y_2\|^2 \leq \\ & \leq \lambda f(x_1) + \lambda \varepsilon + (1-\lambda)f(x_2) + (1-\lambda)\varepsilon \\ & \leq \lambda f(x_1) + (1-\lambda)f(x_2) + \varepsilon \end{aligned}$$

Dall'arbitrarietà di $\varepsilon > 0$ segue la convessità di f

5) $x \mapsto \sup \{ \langle x, y \rangle : y \in C \}$ funzione di supporto di $C \subseteq \mathbb{R}^n$

6) $Q = Q^T \in \mathbb{R}^{n \times n}$ semidefinita positiva

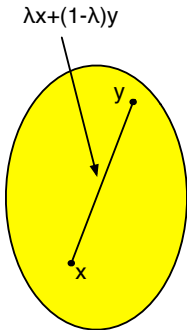
$f(Q) = \sup \{ d^T Q d : \|d\| = 1 \}$ massimo autovalore di Q .

(f definite sull'insieme delle matrici semidef. pos. $\subseteq \mathbb{R}^{2n}$)

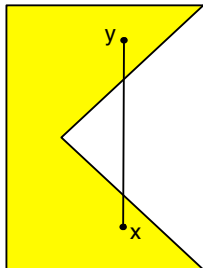
Convexity for sets

$C \subseteq \mathbb{R}^n$ is a **convex set** if

$$x, y \in C, \lambda \in [0, 1] \implies \lambda x + (1 - \lambda)y \in C$$



convex



nonconvex

Operations preserving convexity

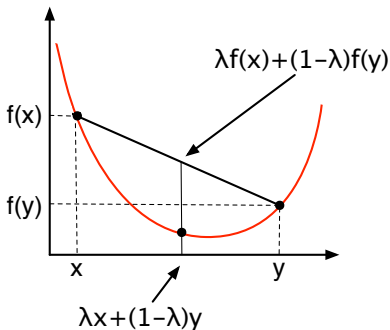
- ▶ Let $C \subseteq \mathbb{R}^n$ be convex.
 - The closure and the (relative) interior of C are convex
- ▶ Let $A \in \mathbb{R}^{m \times n}$.
 - (i) If $C \subseteq \mathbb{R}^n$ is convex, then $A(C) = \{Ax : x \in C\}$ is convex
 - (ii) If $D \subseteq \mathbb{R}^m$ is convex, then $A^{-1}(D) = \{x : Ax \in D\}$ is convex
- ▶ Let $C_i \subseteq \mathbb{R}^{n_i}$ be convex and $\mu_i \in \mathbb{R}$ for all $i \in I$.
 - (i) $\prod_{i \in I} C_i$ is convex
 - (ii) If $n_i = n$, then $\bigcap_{i \in I} C_i$ is convex
 - (iii) If I is finite and $n_i = n$, then $\sum_{i \in I} \mu_i C_i$ is convex

Convexity for functions

Let $C \subseteq \mathbb{R}^n$ be convex. $f : \mathbb{R}^n \rightarrow \mathbb{R}$ is a **convex function on C** if

$$f(\lambda x + (1 - \lambda)y) \leq \lambda f(x) + (1 - \lambda)f(y)$$

holds for all $x, y \in C$, $\lambda \in [0, 1]$.

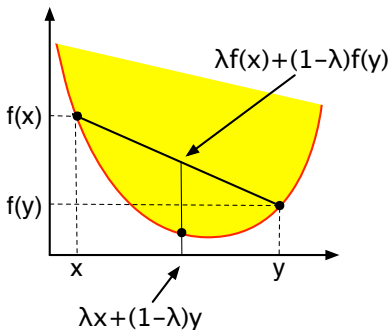


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Proposition

Let $C \subseteq \mathbb{R}^n$ be convex. $f : \mathbb{R}^n \rightarrow \mathbb{R}$ is **convex on C** if and only if (the restriction of) its epigraph (to C), namely

$$\text{epi}(f) \cap (C \times \mathbb{R}) = \{(x, t) \in C \times \mathbb{R} : t \geq f(x)\},$$

is a **convex set** in \mathbb{R}^{n+1} .

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is a **convex set** in \mathbb{R}^{n+1} . Moreover, if f is convex on C , then the (the restriction of) its α -sublevel set (to C), namely

$$S_\alpha(f) \cap C = \{x \in C : f(x) \leq \alpha\},$$

is a convex set in \mathbb{R}^n for any $\alpha \in \mathbb{R}$.

Let $C \subseteq \mathbb{R}^n$ be convex. $f : \mathbb{R}^n \rightarrow \mathbb{R}$ is

- ▶ convex on C if

$$f(\lambda x + (1 - \lambda)y) \leq \lambda f(x) + (1 - \lambda)f(y)$$

holds for all $x, y \in C$, $\lambda \in [0, 1]$

- ▶ strictly convex on C if

$$f(\lambda x + (1 - \lambda)y) < \lambda f(x) + (1 - \lambda)f(y)$$

holds for all $x, y \in C$ with $x \neq y$, $\lambda \in]0, 1[$

- ▶ strongly convex on C with modulus μ if

$$f(\lambda x + (1 - \lambda)y) \leq \lambda f(x) + (1 - \lambda)f(y) - \frac{\mu}{2} \lambda(1 - \lambda) \|x - y\|_2^2$$

holds for all $x, y \in C$, $\lambda \in [0, 1]$

f strongly convex on C if and only if $f - \frac{\mu}{2} \|\cdot\|_2^2$ is convex on C .

Operations preserving convexity

Let $C \subseteq \mathbb{R}^n$ be convex.

► Let $f_i : \mathbb{R}^n \rightarrow \mathbb{R}$ be convex on C and $\mu_i > 0$ for all $i \in I$.

(i) If I is finite, then $\left(\sum_{i \in I} \mu_i f_i\right)(x) = \sum_{i \in I} \mu_i f_i(x)$ is convex on C

(ii) If $\left(\sup_{i \in I} f_i\right)(x) = \sup_{i \in I} f_i(x) < +\infty$ for all $x \in C$, then the pointwise supremum function $\left(\sup_{i \in I} f_i\right)$ is convex on C

► Let $f : \mathbb{R}^n \rightarrow \mathbb{R}$ be convex on \mathbb{R}^n .

(i) $g(x) = f(Ax + b)$ is convex on \mathbb{R}^m for any $A \in \mathbb{R}^{m \times n}$, $b \in \mathbb{R}^n$

(ii) $g(x) = h(f(x))$ is convex on \mathbb{R}^n if $h : \mathbb{R} \rightarrow \mathbb{R}$ is convex and non-decreasing

(iii) $g(x) = h(-f(x))$ is convex on \mathbb{R}^n if $h : \mathbb{R} \rightarrow \mathbb{R}$ is convex and non-increasing

Examples of convex functions

- ▶ $f(x) = \|x\|_2$ (nonsmooth at $x = 0$)
- ▶ $f(x) = \|x\|_2^2$ (smooth)
- ▶ $f(x) = \|x\|_1$ (nonsmooth along the coordinate axes)
- ▶ $f(x) = \frac{1}{2} x^T Q x + b^T x + c$ with $Q = Q^T \in \mathbb{R}^{n \times n}$ positive semidefinite, $b \in \mathbb{R}^n$, $c \in \mathbb{R}$ (strongly convex if Q is positive definite)
- ▶ Let $C \subseteq \mathbb{R}^n$ be convex.
 - (i) $d_C(x) = \min\{\|y - x\|_2 : y \in C\}$ (nonsmooth on the boundary)
 - (ii) $d_C^2(x) = \min\{\|y - x\|_2^2 : y \in C\}$ (smooth)
 - (iii) $\sigma_C(x) = \sup\{y^T x : y \in C\}$ [support function of C]

Convexity and optimization

Let $C \subseteq \mathbb{R}^n$ and $f : \mathbb{R}^n \rightarrow \mathbb{R}$.

$$(P) \quad \min\{f(x) : x \in C\}$$

Suppose C is convex. Then,

- ▶ If f is convex on C , then any **local minimum** point of (P) is also a **global minimum** point. Moreover, the set of all the minima is a convex set.
- ▶ If f is **strictly convex** on C , there exists **at most one** minimum point of (P).
- ▶ If f is **strongly convex** on C , there exists **exactly one** minimum point of (P).

Differentiable convex functions

Let $C \subseteq \mathbb{R}^n$ be convex and $f : \mathbb{R}^n \rightarrow \mathbb{R}$ differentiable on C .

(i) f is (strictly) convex on C if and only if

$$f(y) \geq f(x) + \nabla f(x)^T (y - x) \quad (>)$$

or equivalently

$$(\nabla f(x) - \nabla f(y))^T (x - y) \geq 0 \quad (>)$$

holds for all $x, y \in C$ (with $x \neq y$).

Differentiable convex functions

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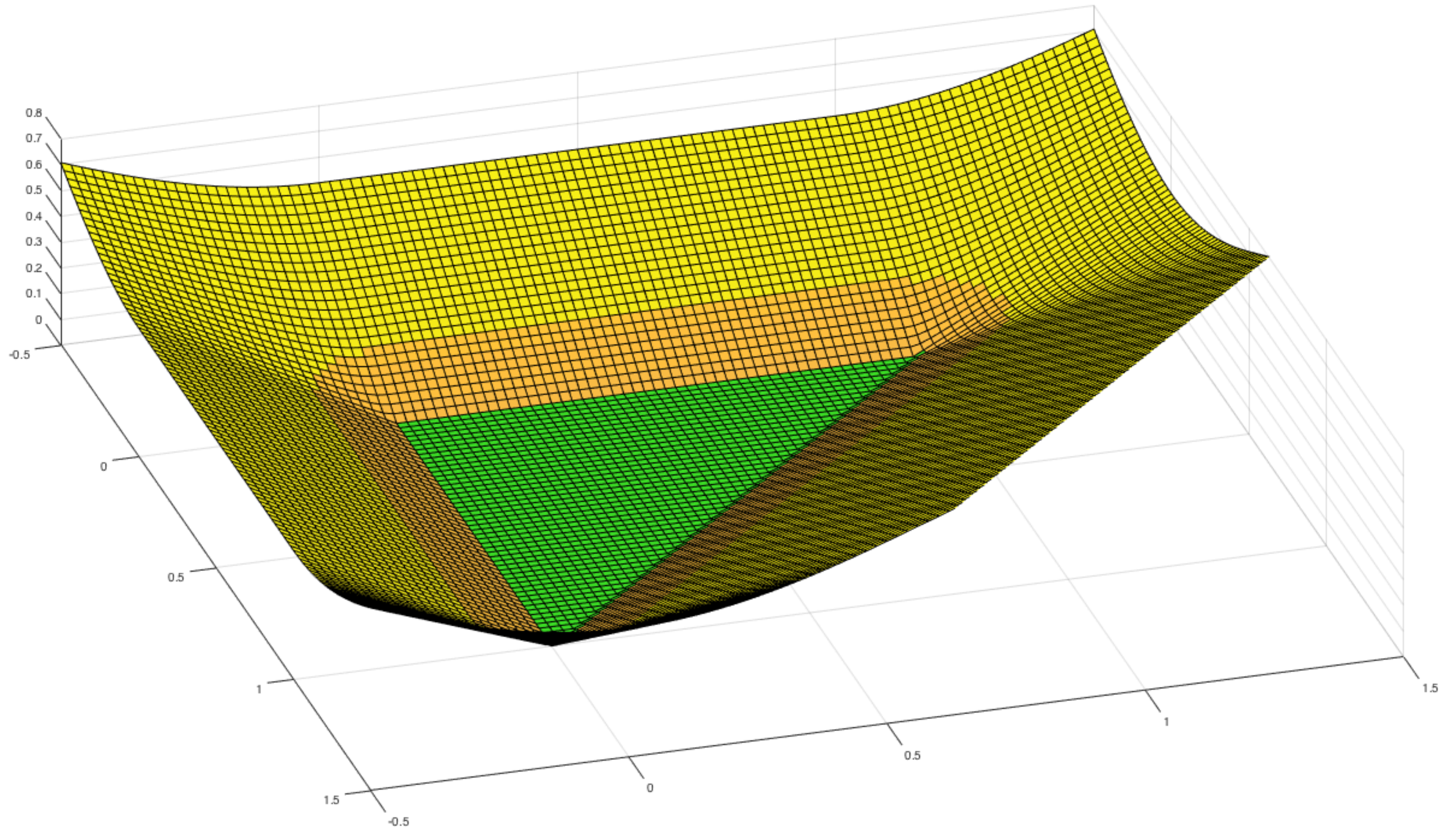
(ii) f is strongly convex on C with modulus $\mu > 0$ if and only if

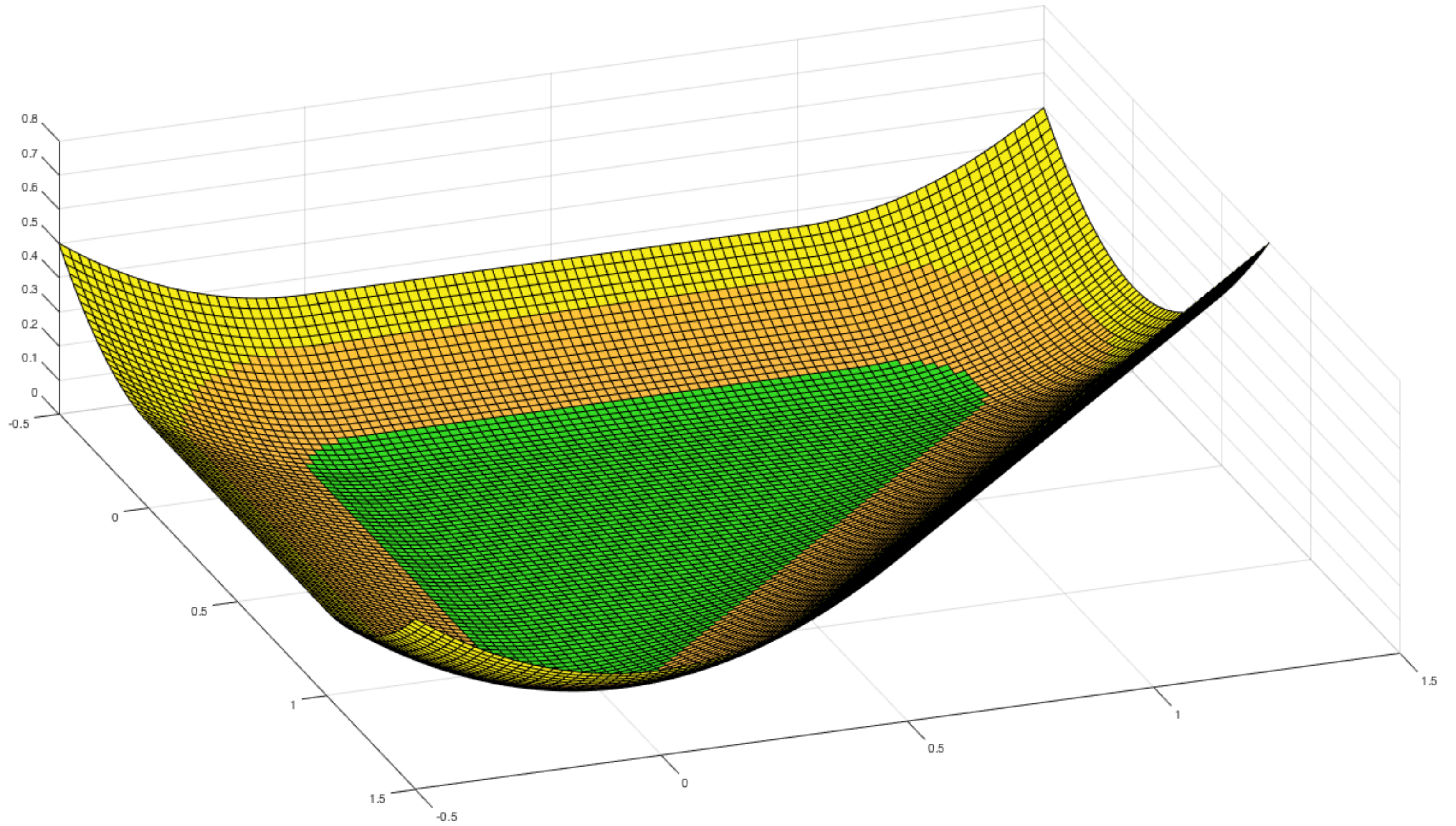
$$f(y) \geq f(x) + \nabla f(x)^T (y - x) + \frac{\mu}{2} \|y - x\|_2^2$$

or equivalently

$$(\nabla f(x) - \nabla f(y))^T (x - y) \geq \mu \|y - x\|_2^2$$

holds for all $x, y \in C$.





Mean value theorem

Let f be convex on \mathbb{R}^n . Given any $x, y \in \mathbb{R}^n$ with $x \neq y$, then

- ▶ there exist $\lambda \in]0, 1[$ and $s_\lambda \in \partial f(\lambda x + (1 - \lambda)y)$ such that

$$f(y) - f(x) = s_\lambda^T (y - x)$$

- ▶ $f(y) - f(x) = \int_0^1 s_\lambda^T (y - x) d\lambda$

for any choice of the subgradients $s_\lambda \in \partial f(\lambda x + (1 - \lambda)y)$

Calculus rules

Let $f, f_i: \mathbb{R}^n \rightarrow \mathbb{R}$ be convex on \mathbb{R}^n for all $i \in I$ [\leftarrow finite index set]

▶ $\partial(\alpha f)(x) = \alpha \partial f(x)$ for all $\alpha > 0$

▶ $\partial\left(\sum_{i \in I} f_i\right)(x) = \sum_{i \in I} \partial f_i(x)$

▶ Let $I(x) = \{j \in I : f_j(x) = \max_{i \in I} f_i(x)\}$

$$\partial\left(\max_{i \in I} f_i\right)(x) = \text{conv} \bigcup_{i \in I(x)} \partial f_i(x)$$

▶ Let $A \in \mathbb{R}^{n \times m}$, $b \in \mathbb{R}^n$, $g(x) = f(Ax + b)$

$$\partial g(x) = A^T \partial f(Ax + b)$$

▶ Let $h: \mathbb{R} \rightarrow \mathbb{R}$ be convex, non-decreasing and differentiable

$$\partial(h \circ f)(x) = h'(f(x)) \partial f(x)$$