

Convex Optimisation

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ACE Network

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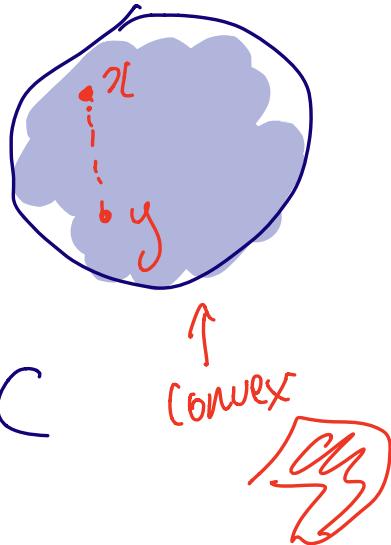
Course webpage:

matthewktam.github.io/cvxopt

Last time

- convex set:

$$x, y \in C \text{ and } \lambda \in [0, 1] \\ \Rightarrow \lambda x + (1 - \lambda)y \in C$$



- convex function

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

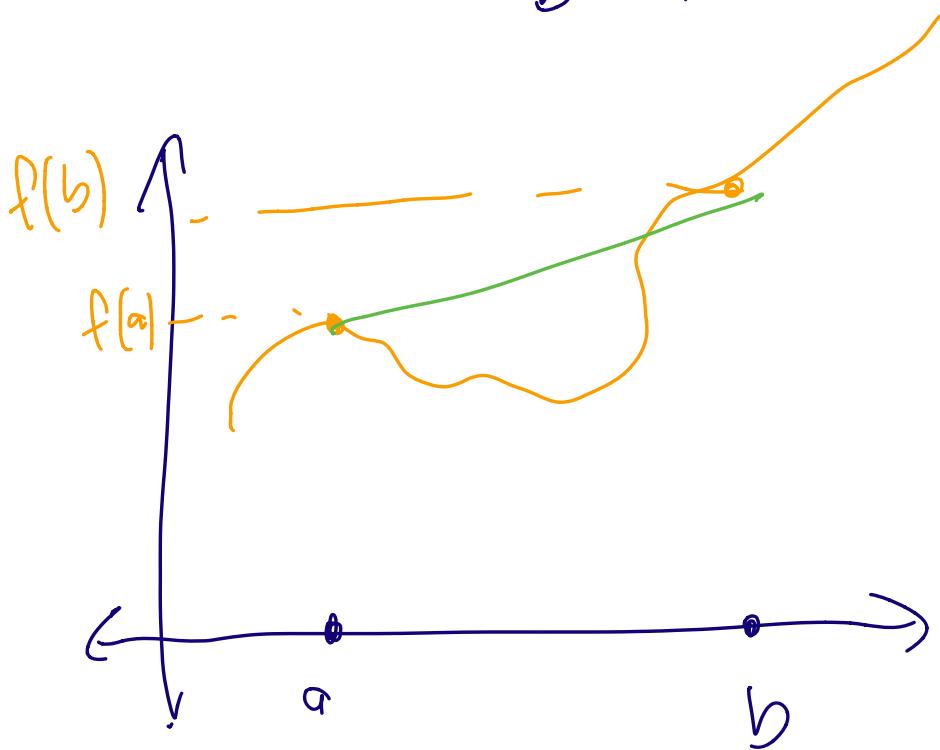


$f + \lambda g$ is convex if f, g convex
and $\lambda \geq 0$.

Mean value theorem

Let $f: [a, b] \rightarrow \mathbb{R}$ be a continuous function which is differentiable on (a, b) . Then $\exists c \in (a, b)$ such that

$$f'(c) = \frac{f(b) - f(a)}{b - a}$$



2.2 Differentiability of convex functions.

Lemma 2.2.1

Let $f: I \rightarrow \mathbb{R}$ where $I \subseteq \mathbb{R}$ is an interval. Then:

- (a) Suppose f is differentiable. Then f is convex iff f' is nondecreasing.
- (b) Suppose f is twice differentiable. Then f is convex iff $f''(x) \geq 0 \quad \forall x \in I$.

Pf (a) Let $x, y \in I$ and $\lambda \in (0, 1)$.

Since f is convex, we have

$$\begin{aligned} f(y) + \lambda(f(x) - f(y)) &= \lambda f(x) + (1-\lambda)f(y) \\ &\geq f(\lambda x + (1-\lambda)y) \\ &= f(y + \lambda(x-y)) \end{aligned}$$

Rearranging and taking the limit
as $\lambda \rightarrow 0$ gives

$$\begin{aligned} f(x) - f(y) &\geq \dim_{\lambda \rightarrow 0} \frac{f(y + \lambda(x-y)) - f(y)}{\lambda} \\ &= \left(\dim_{\lambda \rightarrow 0} \frac{f(y + \lambda(x-y)) - f(y)}{\lambda(x-y)} \right)^{(x-y)} \\ &= f'(y)(x-y). \quad \textcircled{*} \end{aligned}$$

Interchanging the roles of x, y , we obtain

$$f(y) - f(x) \geq f'(x)(y-x). \quad \text{(*)}$$

Adding ~~(*)~~ and ~~(**)~~ together gives

$$\begin{aligned} 0 &\geq f'(y)(x-y) + f'(x)(y-x) \\ &= (f'(x) - f'(y))(y-x) \end{aligned}$$

Thus, if $x \geq y$, then $f'(x) \geq f'(y)$.
In other words, f' is non-decreasing.

Conversely, suppose f is not convex on I . Then there exist $x, y \in I$ and $t \in (0, 1)$

such that

$$\begin{aligned} f(tx + (1-t)y) \\ > tf(x) + (1-t)f(y) \end{aligned}$$

Let $z := tx + (1-t)y = y - t(y-x)$

Then

$$t = \frac{y-z}{y-x} \text{ and } 1-t = \frac{z-x}{y-x}$$

Thus, altogether, we have

$$\begin{aligned} f(z) &> \frac{y-z}{y-x} f(x) \\ &\quad + \frac{z-x}{y-x} f(y) \end{aligned}$$

which implies

$$\frac{f(z) - f(x)}{z - x} > \frac{f(y) - f(z)}{y - z}.$$

By the mean value theorem,

$\exists u \in [x, z]$ and $v \in [z, y]$
such that

$$f'(u) = \frac{f(z) - f(x)}{z - x} > \frac{f(y) - f(z)}{y - z} = f'(v)$$

i.e. $f'(u) > f'(v)$, but $u \leq v$

Thus f' is not nondecreasing.

(b) Since f' is nondecreasing

if f'' is nonnegative, the
result follows from (a). □

Example 2.2.2

The functions $f(x) = e^x$ and $g(x) = -\log(x)$ are convex on their domains.

Pf $f''(x) = e^x > 0 \quad \forall x \in \mathbb{R}$

So convex by Lemma 2.2.1(b).

$$g''(x) = \frac{1}{x^2} > 0 \quad \forall x > 0$$

So convex by Lemma 2.2.1(b).

The function $h(x) = x \log(x)$ is convex on $\mathbb{R}_{++} = (0, +\infty)$.

Pf $h''(x) = \frac{1}{x^2} > 0$ for all $x > 0$.

So convex by Lemma 2.2.1(b).

Recall that the gradient of a function $f: \mathbb{R}^n \rightarrow \mathbb{R}$ at a point $x \in \mathbb{R}^n$ is given by

$$\nabla f(x) = \left(\begin{array}{c} \frac{\partial f}{\partial x_1}(x) \\ \frac{\partial f}{\partial x_2}(x) \\ \vdots \\ \vdots \\ \frac{\partial f}{\partial x_n}(x) \end{array} \right)$$

when it exists, it satisfies

$$D_f(x; h) \parallel$$

$$\lim_{t \rightarrow 0} \frac{f(x+th) - f(x)}{t} = \langle \nabla f(x), h \rangle$$

The Hessian of f at x is

the matrix $\nabla^2 f(x) \in \mathbb{R}^{n \times n}$ whose i,j -th coordinate is given

$$[\nabla^2 f(x)]_{ij} = \frac{\partial^2 f}{\partial x_i \partial x_j}(x)$$

Proposition 2.2.3

Let $f: U \rightarrow \mathbb{R}$ where $U \subseteq \mathbb{R}^n$ is an open set. Then the following hold.

(a) Suppose f is differentiable.

Then f is convex iff

(2.1)

$$f(x) \geq f(y) + \langle \nabla f(y), x - y \rangle \quad \forall x, y \in U$$

(b) Suppose f is twice differentiable.

Then f is convex iff

$$\nabla^2 f(x) \succeq 0 \quad \forall x \in \mathcal{J}$$

\uparrow
 $\equiv \nabla^2 f(x)$ is positive
semi-definite.

\equiv eigenvalues of $\nabla^2 f(x)$
nonnegative.

Pf(a). Let $x, y \in \mathcal{J}$ and $\lambda \in (0, 1)$. Then,
by convexity of f , we have

$$\begin{aligned} & f(y) + \lambda(f(x) - f(y)) \\ &= \lambda f(x) + (1-\lambda)f(y) \\ &\geq f(\lambda x + (1-\lambda)y) \\ &= f(y + \lambda(x-y)). \end{aligned}$$

Rearranging and taking the limit as
 $\lambda \rightarrow 0$ gives

$$f(x) - f(y) \geq \lim_{\lambda \rightarrow 0} \frac{f(y + \lambda(x-y)) - f(y)}{\lambda}$$
$$= \langle \nabla f(y), x-y \rangle.$$

which establishes (2.1).

Conversely, suppose (2.1) holds. Then
for all $x, y \in \mathcal{O}$, we have

$$f(x) \geq f(y) + \langle \nabla f(y), x-y \rangle, \text{ and}$$
$$f(y) \geq f(x) + \langle \nabla f(x), y-x \rangle.$$

Summing these two inequalities
together gives

$$0 \geq \langle \nabla f(y), x - y \rangle + \langle \nabla f(x), y - x \rangle$$

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

$\forall x, y \in U$ [2.2]

Let $x, y \in U$ be arbitrary. To establish convexity of f , it suffices to show that $g: [0, 1] \rightarrow \mathbb{R}$ is convex where g is given by

$$\begin{aligned} g(t) &:= f((1-t)x + ty) \\ &= f(x + t(y-x)) \end{aligned}$$

Aside:

$$g'(t) = \lim_{a \rightarrow 0} \frac{g(t+a) - g(t)}{a}$$

$$= \lim_{\alpha \rightarrow 0} \frac{f(x + t(y-x) + \alpha(y-x)) - f(x + t(y-x))}{\alpha}$$

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

Using (2.2), we deduce

$$(g'(t) - g'(s)) (t-s)$$

$$= \langle \nabla f(x + t(y-x)) - \nabla f(x + s(y-x)), y-x \rangle$$

$$= \langle \nabla f(x + t(y-x)) - \nabla f(x + s(y-x)), [x + t(y-x)] - [x + s(y-x)] \rangle$$

$$= (t-s)(y-x)$$

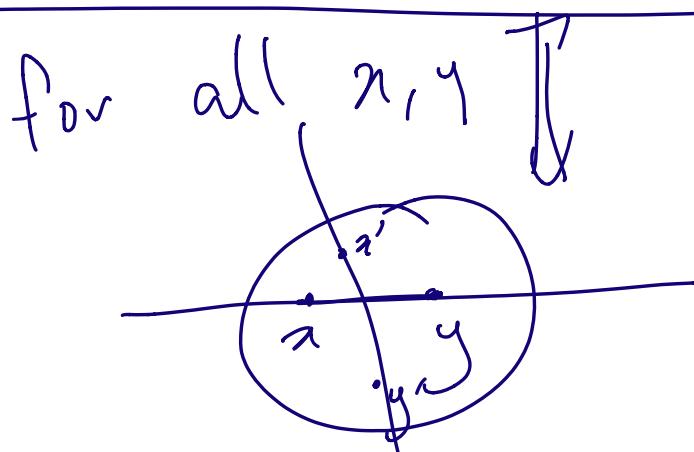
≥ 0 (by (2.2)).

If $t > s$, then $\underline{g'(t) \geq g'(s)}$,
 That is, g' is non increasing on $[0, 1]$
 $\Rightarrow g$ is convex by Lemma 2.2.1(a),
 Hence, the result follows.

(b) Exercise assignment 2.

E

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



Definition 2.2.4

An operator $T: \mathbb{R}^n \rightarrow \mathbb{R}^n$ is

L -Lipschitz continuous (where $L \geq 0$)

If

$$\|T(x) - T(y)\| \leq L \|x - y\| \quad \forall x, y \in \mathbb{R}^n.$$

Proposition 2.2.5 (descend lemma)

Let $f: \mathbb{R}^n \rightarrow \mathbb{R}$ be a differentiable convex function with L -Lipschitz continuous gradient. Then

$$f(y) \leq f(x) + \langle \nabla f(z), y - x \rangle + \frac{L}{2} \|y - z\|^2$$
$$\quad \forall x, y, z \in \mathbb{R}^n.$$

Pf. Let $x, y, z \in \mathbb{R}^n$ and set

$$\phi(t) := f(z + t(y-z)), \quad t \in [0, 1].$$

Since f is differentiable, we have:

$$\phi'(t) = \langle y-z, \nabla f(z+t(y-z)) \rangle$$

By the Fundamental Theorem of Calculus applied to ϕ , we have

$$\phi(1) - \phi(0) = \int_0^1 \phi'(t) dt$$

Thus, we have

$$f(y) - f(z)$$

$$= \int_0^1 \langle y-z, \nabla f(z+t(y-z)) \rangle dt$$

$$= \int_0^1 \langle y-z, \nabla f(z+t(y-z)) - \nabla f(z) \rangle$$

$$+ \langle y-z, \nabla f(z) \rangle dt$$

$$= \int_0^1 \langle y-z, \nabla f(z+t(y-z)) - \nabla f(z) \rangle dt$$

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

$$= \int_0^1 \frac{1}{t} \langle z + t(y-z) - z, \nabla f(z+t(y-z)) - \nabla f(z) \rangle dt$$

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

\leq

$$\int_0^1 \frac{1}{t} \|t(y-z)\| \| \nabla f(z+t(y-z)) - \nabla f(z) \| dt$$

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

\leq

$$\int_0^1 \frac{1}{t} \|t(y-z)\| \cdot L \|z + t(y-z) - z\| dt$$

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

$$= \int_0^1 t L \|y-z\|^2 dt + \langle y-z, \nabla f(z) \rangle$$

$$= \frac{\mu}{2} \|y - z\|^2 + \langle y - z, \nabla f(z) \rangle$$

Altogether, we have.

$$f(y) \leq f(z) + \langle \nabla f(z), y - z \rangle + \frac{\mu}{2} \|y - z\|^2 \quad \textcircled{F}$$

Since f is differentiable and convex,
Proposition 2.2.3(a) implies

$$f(z) + \langle \nabla f(z), x - z \rangle \leq f(x) \quad (\text{ie. } \textcircled{W})$$

$$\Rightarrow 0 \leq f(x) - f(z) + \langle \nabla f(z), z - x \rangle \quad \textcircled{*}$$

Adding \textcircled{F} and $\textcircled{*}$ gives.

$$f(y) \leq f(x) + \langle \nabla f(z), y - x \rangle + \frac{\mu}{2} \|y - z\|^2.$$

Which completes the proof. \square .

Example 2.2.6

Let $f(x) = \frac{1}{2} \|x\|^2$. Then $Df(x) = x$.

which is 1-Lipschitz cont since

$$\begin{aligned}\|Df(x) - Df(y)\| &= \|x - y\| \\ &\leq L \|x - y\|\end{aligned}$$

with $L = 1$.