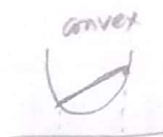


# \* Concave and convex functions

(Def) Let  $C \subseteq \mathbb{R}^n$  be convex



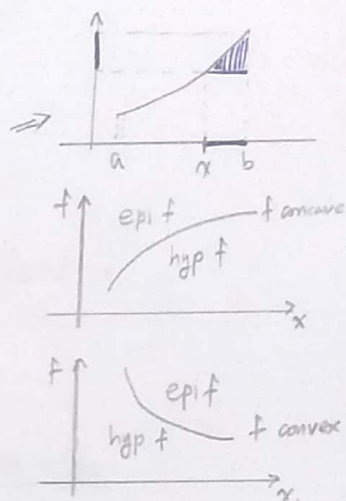
The function  $f: C \rightarrow \mathbb{R}$  is (strictly) convex

if for all  $x, x' \in C$  and  $\lambda \in [0, 1]$ ,  $(1-\lambda)f(x) + \lambda f(x') \geq f((1-\lambda)x + \lambda x')$   
 $(\lambda \in (0, 1))$

The function  $f: C \rightarrow \mathbb{R}$  is (strictly) concave if  $-f$  is (strictly) convex

The hypograph of the function  $f: C \rightarrow \mathbb{R}$  is defined as

$$\text{hyp } f := \{ (x, y) \in \mathbb{R}^{n+1} \mid x \in C \text{ and } f(x) \geq y \}$$



The epigraph of the function  $f: C \rightarrow \mathbb{R}$  is defined as

$$\text{epi } f := \{ (x, y) \in \mathbb{R}^{n+1} \mid x \in C \text{ and } f(x) \leq y \}$$

(Thm 5.7) Let  $C \subseteq \mathbb{R}^n$  be convex and  $f: C \rightarrow \mathbb{R}$ . The  $f$  is convex (concave)

if and only if its epigraph (hypograph) is convex.

proof)  $(\Rightarrow)$  Let  $f$  is concave.  $(x, y)$  and  $(x', y') \in \text{hyp } f$ , and  $\lambda \in [0, 1]$ .

$$\text{Then } y^\lambda := (1-\lambda)y + \lambda y' \leq (1-\lambda)f(x) + \lambda f(x') \leq f((1-\lambda)x + \lambda x') = f(x^\lambda)$$

This implies that  $(x^\lambda, y^\lambda) \in \text{hyp } f$

$(\Leftarrow)$  Suppose the hypograph is convex.

Given arbitrary  $x, x' \in C$  and  $\lambda \in [0, 1]$ ,

$(x, f(x))$  and  $(x', f(x'))$  lie in the hypograph.

Setting  $x^\lambda := (1-\lambda)x + \lambda x'$ , we get  $(x^\lambda, (1-\lambda)f(x) + \lambda f(x'))$  lies in the hypograph. Therefore,  $(1-\lambda)f(x) + \lambda f(x') \leq f(x^\lambda)$

Since this holds for arbitrary  $x, x' \in C$ , and  $\lambda \in [0, 1]$ ,  $f$  is concave.  $\parallel$

**Thm 58** Let  $C \subseteq \mathbb{R}^n$  be convex and  $f: C \rightarrow \mathbb{R}$  be concave

If  $x^*$  is a local maximizer of  $f$ ,

then it is a global " that is  $f(x) \leq f(x^*)$  for all  $x \in C$ .

proof) Fix an arbitrary  $x \in C$ .

Since  $x^*$  is a local maximizer, we get that for  $\lambda > 0$  small enough

$$f(x^*) \geq f((1-\lambda)x^* + \lambda x) \geq (1-\lambda)f(x^*) + \lambda f(x)$$

Rearranging this, we get that  $f(x^*) \geq f(x)$ . ||

$$(\because f(x^*) \geq (1-\lambda)f(x^*) + \lambda f(x))$$

$$\downarrow$$
  

$$\lambda f(x^*) \geq \lambda f(x) \text{ i.e., } f(x^*) \geq f(x)$$

**Def** Let  $X \subseteq \mathbb{R}^n$ .  $x \in X$  is an extreme point of  $X$

if there are no distinct  $x_1, x_2 \in X$  such that  $x = \frac{x_1 + x_2}{2}$ .

**Thm 59** Let  $C \subseteq \mathbb{R}^n$  be convex,  $X \subseteq C$ , and let  $f: C \rightarrow \mathbb{R}$  be strictly convex.

If  $x^*$  maximizes  $f$  over  $X$ , then it is an extreme point of  $X$ .

In particular, if  $X$  is compact, then the set of extreme points is non-empty.

proof) Suppose for contradiction that  $x^*$  is not an extreme point of  $X$ .

Then there exist  $x_1, x_2 \in X$  such that  $x_1 \neq x_2$  and  $x^* = \frac{x_1 + x_2}{2}$ .

Thus,  $f(x^*) < \frac{1}{2} [f(x_1) + f(x_2)]$  because  $f$  is strictly convex.

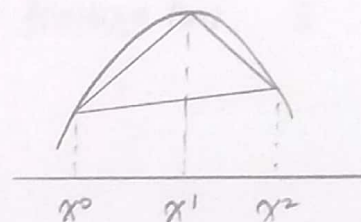
This contradicts optimality of  $x^*$ . If  $X$  is compact, the Extreme Value thm implies that every continuous function  $f$  achieves maximum over  $X$  at some  $x^* \in X$ . If  $f$  is in addition strictly convex, (as for example  $f(x) = \|x\|^2$ ) then the first part implies that  $x^*$  is an extreme point of  $X$ . ||

Lemma II (Three-chord-lemma)

Let  $[a, b] \subseteq \mathbb{R}$ ,  $x^0, x^1, x^2 \in (a, b)$  satisfy  $x^0 < x^1 < x^2$  and let  $f: [a, b] \rightarrow \mathbb{R}$  be concave. Given  $x, y \in [a, b]$  satisfying  $x \neq y$  define  $S(x, y) = \frac{f(y) - f(x)}{y - x}$ .

Then,  $S(x^0, x^1) \geq S(x^0, x^2) \geq S(x^1, x^2)$

proof)  $x^1 = \frac{x^2 - x^0}{x^2 - x^0} x^0 + \frac{x^1 - x^0}{x^2 - x^0} x^2$



Then,  $f(x^1) \geq \frac{x^2 - x^1}{x^2 - x^0} f(x^0) + \frac{x^1 - x^0}{x^2 - x^0} f(x^2)$  by concavity.

which implies  $f(x^1) - f(x^0) \geq \frac{x^1 - x^0}{x^2 - x^0} [f(x^2) - f(x^0)]$

Hence we get the first inequality. The second follows similarly. ||

Thm 60 Let  $[a, b] \subseteq \mathbb{R}$  and  $f: [a, b] \rightarrow \mathbb{R}$  be concave

For any  $x, y \in \mathbb{R}$  satisfying  $a < x < y < b$ , the one-sided derivative,

$$f'_+(x) := \lim_{h \downarrow 0} \frac{f(x+h) - f(x)}{h}$$

$$f'_-(x) := \lim_{h \uparrow 0} \frac{f(x+h) - f(x)}{h} \text{ exist and satisfy}$$

$$f'_-(x) \geq f'_+(x) \geq \frac{f(y) - f(x)}{y - x} \geq f'_-(y) \geq f'_+(y)$$

proof) HW. (HINT: Lemma II)



Thm 61 Let  $[a, b] \subseteq \mathbb{R}$  and  $f: [a, b] \rightarrow \mathbb{R}$  be concave.

Then  $f$  is continuous on  $[a, b]$

proof) Fix  $x \in (a, b)$ . Then  $\lim_{h \downarrow 0} f(x+h) - f(x) = \lim_{h \downarrow 0} \frac{f(x+h) - f(x)}{h} \cdot \lim_{h \downarrow 0} h = 0$

The analogous argument for  $h \uparrow 0$  yields  $\lim_{h \rightarrow 0} f(x+h) = f(x)$ .  $\parallel$

### Lemma 13

Let  $(a, b) \subseteq \mathbb{R}$  and  $f: (a, b) \rightarrow \mathbb{R}$  be twice continuously differentiable

Then  $f$  is concave if and only if  $f''(x) \leq 0$  for all  $x \in (a, b)$

proof) :  $(\Rightarrow)$  follows from the three-chord lemma  $\parallel$ .

$(\Leftarrow)$  Since  $f$  is twice continuously differentiable and  $f''(x) \leq 0$ , this implies (Problem set 8)  $f'(x)$  is monotone decreasing.

Given arbitrary  $x, x' \in (a, b)$  satisfying  $x < x'$  and  $\lambda \in (0, 1)$ ,

We set  $x^\lambda = (1-\lambda)x + \lambda x'$

$$\begin{aligned} \text{Then, } \frac{f(x^\lambda) - f(x)}{x^\lambda - x} &\geq \inf_{t \in (x, x^\lambda)} f'(t) \geq \sup_{t \in (x^\lambda, x')} f'(t) \geq \frac{f(x') - f(x^\lambda)}{x' - x^\lambda} \\ &\quad \uparrow \text{(mean value thm)} \quad \uparrow \text{Lemma 11} \quad \uparrow \text{(Mean value thm)} \end{aligned}$$

here the first and last inequality follow from the mean value thm.

Note that  $x^\lambda - x = \lambda(x' - x)$  and  $x' - x^\lambda = (1-\lambda)(x' - x)$

This yields

$$\begin{aligned} (1-\lambda)(f(x^\lambda) - f(x)) &\geq \lambda(f(x') - f(x^\lambda)) \\ \text{or} \quad f(x^\lambda) &\geq (1-\lambda)f(x) + \lambda f(x') \quad \parallel \\ &\quad \text{(f is concave)} \end{aligned}$$

**Def** An  $n \times n$  matrix is negative (semi) definite

if for all  $x \in \mathbb{R}^n$ ,  $x^T A x < 0$   
 $(\leq)$

An  $n \times n$  matrix is positive (semi) definite

if for all  $x \in \mathbb{R}^n$ ,  $x^T A x > 0$   
 $(\geq)$

twice continuously differentiable

Let  $X \subseteq \mathbb{R}^n$  be open if  $f: X \rightarrow \mathbb{R}$  is of class  $C^2$

Then its Hessian Matrix  $D^2 f(x)$  is defined by

$$D^2 f(x) := D \nabla f(x) = \left[ \frac{\partial^2 f}{\partial x_i \partial x_j} \right]_{i,j}$$

**Thm 6.2** Let  $X \subseteq \mathbb{R}^n$  be open and convex and let  $f: X \rightarrow \mathbb{R}$  be in  $C^2$ .

Then,  $f$  is concave if and only if the Hessian matrix  $D^2 f(x)$  is negative semi definite,  $\forall x \in X$ .

## \* Optimization

Consider constraint optimization problem

$$\max_x f(x, \alpha) \quad \text{subject to } x \in C(\alpha)$$

$x$  : choice variable

$\alpha$  : a parameter

$f$  : the objective function

$C(\alpha)$  : the constraint set

We define the value function and decision values as

$$V(\alpha) := \max_{x \in C(\alpha)} f(x, \alpha)$$

$$S(\alpha) := \{y \in C(\alpha) \mid f(y, \alpha) = \max_{x \in C(\alpha)} f(x, \alpha)\}$$

→ Lagrangian thm for equality constraints

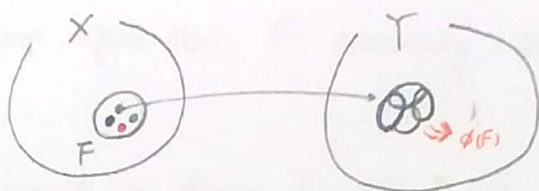
→ Karush-Kuhn-Tucker thm for inequality constraints

# \* Theorem of the maximum

(Def) Let  $X, Y$  be metric spaces

A correspondence  $\phi$  from  $X$  to  $Y$ ,  $\phi: X \rightrightarrows Y$  associates to each  $x \in X$  a subset of  $Y$ .

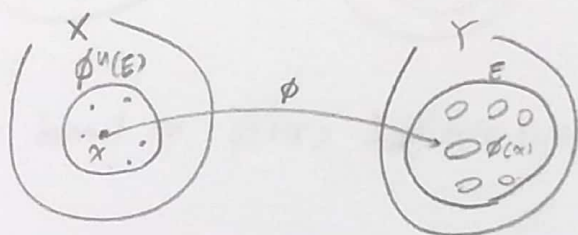
(Def): The image of  $F \subseteq X$  under  $\phi$  is defined by  $\phi(F) := \bigcup_{x \in F} \phi(x)$



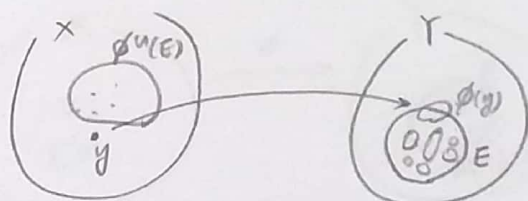
"Totally contained"

- The upper inverse of  $E \subseteq Y$  under  $\phi$  is defined by  $\phi^u[E] = \{x \in X \mid \phi(x) \subseteq E\}$
- The lower inverse of  $E \subseteq Y$  under  $\phi$  is defined by  $\phi^l[E] = \{x \in X \mid \phi(x) \cap E \neq \emptyset\}$

"partially contained"

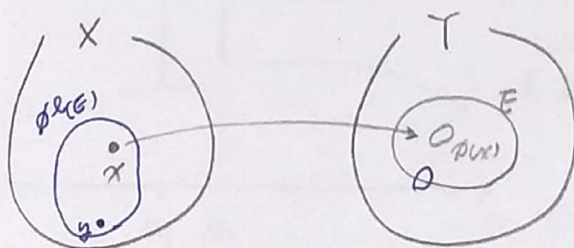


Totally contained



partially contained

Thus,  $y \notin \phi^u(E)$



$y \in \phi^l(E)$



$E$  is upper bound on  $\phi(x)$  ②

(Def) • A correspondence  $\phi : X \rightrightarrows Y$  is upper hemi-continuous at  $x$  if  $\phi(x) \subseteq E$

if whether  $x$  is in the upper inverse of an open set  $E \subseteq Y$

there is an open set  $F$  containing  $x$  that satisfies  $F \subseteq \phi^{-1}(E)$

• A correspondence  $\phi : X \rightrightarrows Y$  is lower hemi-continuous at  $x$

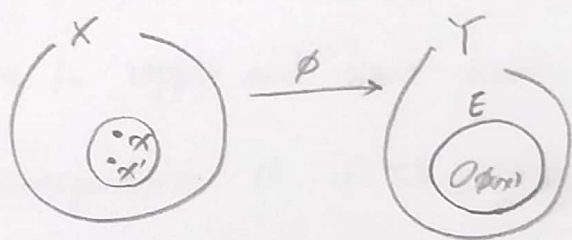
Whenever  $x$  is in the lower inverse of an open set  $E \subseteq Y$ ,

there is an open set  $F$  containing  $x$  that satisfies  $F \subseteq \phi^{-1}(E)$

$E$  is ~~upper~~ lower bound on  $\phi(x)$ .

$\phi(x') \cap E \neq \emptyset$

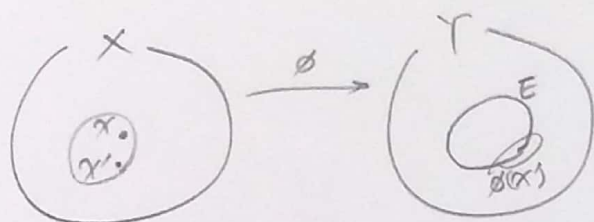
$\Rightarrow E$  is upper bound on  $\phi(x)$  for  $x' \in B_\epsilon(x)$ :  $\phi(x') \subseteq E$



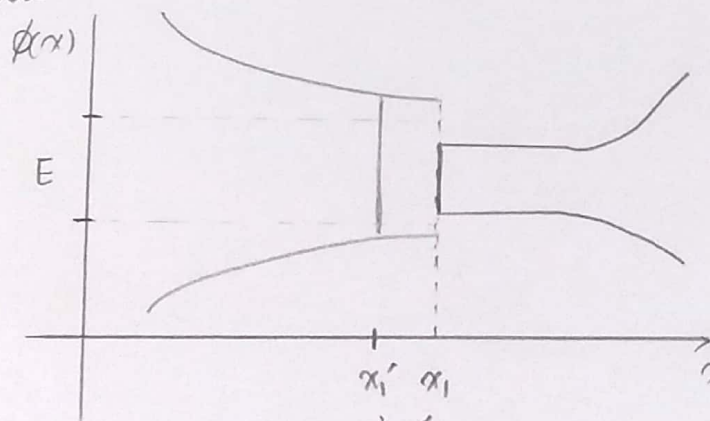
$x \rightarrow x'$  close,  $E \rightarrow \phi(x)$  close

$\Rightarrow E$  is lower bound on  $\phi(x)$  for  $x' \in B_\epsilon(x)$  :

$\phi(x') \cap E \neq \emptyset$



& pictures!

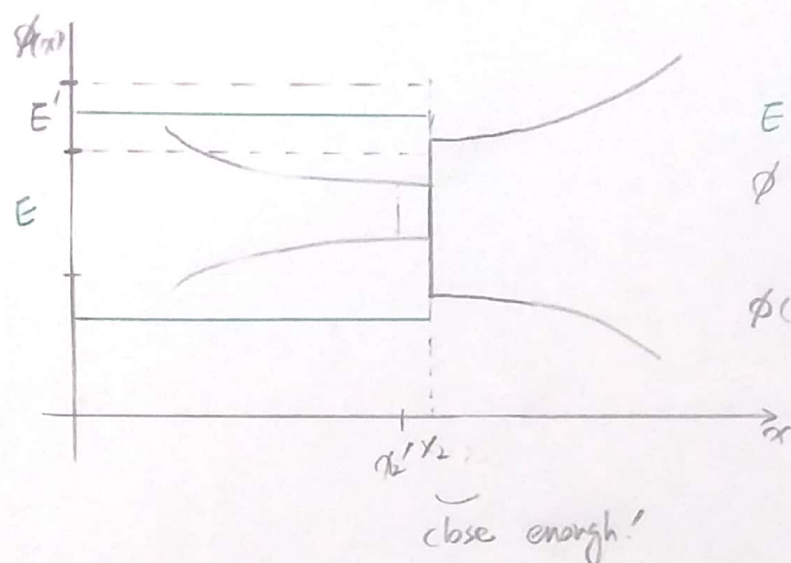


$E \supseteq \phi(x_1)$  but  $E \not\supseteq \phi(x'_1)$  :  $\phi$  is not lhc in  $x_1$

$x \in E \cap \phi(x'_1) \neq \emptyset$  :  $\phi$  is lhc in  $x_1$

close enough!





$E \supset \phi(x_2')$  also  $\phi(x_2)$

$\phi$  is uhc at  $x_2$

$\phi(x_2') \cap E' = \emptyset$  :  $\phi$  is not lhc at  $x_2$

- (Def) • A correspondence  $\phi : X \rightrightarrows Y$  is continuous at  $x$  if it is upper and lower hemicontinuous at  $x$ .
- A correspondence  $\phi : X \rightrightarrows Y$  is compact-valued at  $x$  if  $\phi(x)$  is compact.