

**Mathematical Economics**

# **Convex Analysis (II)**

**Kui Ou-Yang**

**School of Economics & Management  
Northwest University**

# Concave and Convex Functions

For any nonempty convex set  $X \subseteq \mathbb{R}^n$ , a function  $f: X \rightarrow \mathbb{R}$  is

- **concave** if  $\forall x, y \in X, \forall \lambda \in [0, 1]$ ,
$$f(\lambda x + (1-\lambda)y) \geq \lambda f(x) + (1-\lambda)f(y).$$
- **convex** if  $\forall x, y \in X, \forall \lambda \in [0, 1]$ ,
$$f(\lambda x + (1-\lambda)y) \leq \lambda f(x) + (1-\lambda)f(y).$$
- **strictly concave** if  $\forall x, y \in X$  with  $x \neq y, \forall \lambda \in (0, 1)$ ,
$$f(\lambda x + (1-\lambda)y) > \lambda f(x) + (1-\lambda)f(y).$$
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$$f(\lambda x + (1-\lambda)y) < \lambda f(x) + (1-\lambda)f(y).$$
- Obviously,  $f$  is concave iff  $-f$  is convex, and  $f$  is strictly concave iff  $-f$  is strictly convex.

# Quasi-concave and Quasi-convex Functions

For any nonempty convex set  $X \subseteq \mathbb{R}^n$ , a function  $f: X \rightarrow \mathbb{R}$  is

- *quasi-concave* if  $\forall x, y \in X, \forall \lambda \in [0, 1]$ ,  
$$f(\lambda x + (1-\lambda)y) \geq \min\{f(x), f(y)\};$$
- *quasi-convex* if  $\forall x, y \in X, \forall \lambda \in [0, 1]$ ,  
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$$f(\lambda x + (1-\lambda)y) \leq \max\{f(x), f(y)\};$$
- ***strictly quasi-concave*** if  $\forall x, y \in X$  with  $x \neq y, \forall \lambda \in (0, 1)$ ,  
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$$f(\lambda x + (1-\lambda)y) < \max\{f(x), f(y)\}.$$

Obviously,  $f$  is quasi-concave iff  $-f$  is quasi-convex, and  $f$  is strictly quasi-concave iff  $-f$  is strictly quasi-convex.

Note that a (strictly) concave (convex) function must be (strictly) quasi-concave (quasi-convex), but not vice versa.

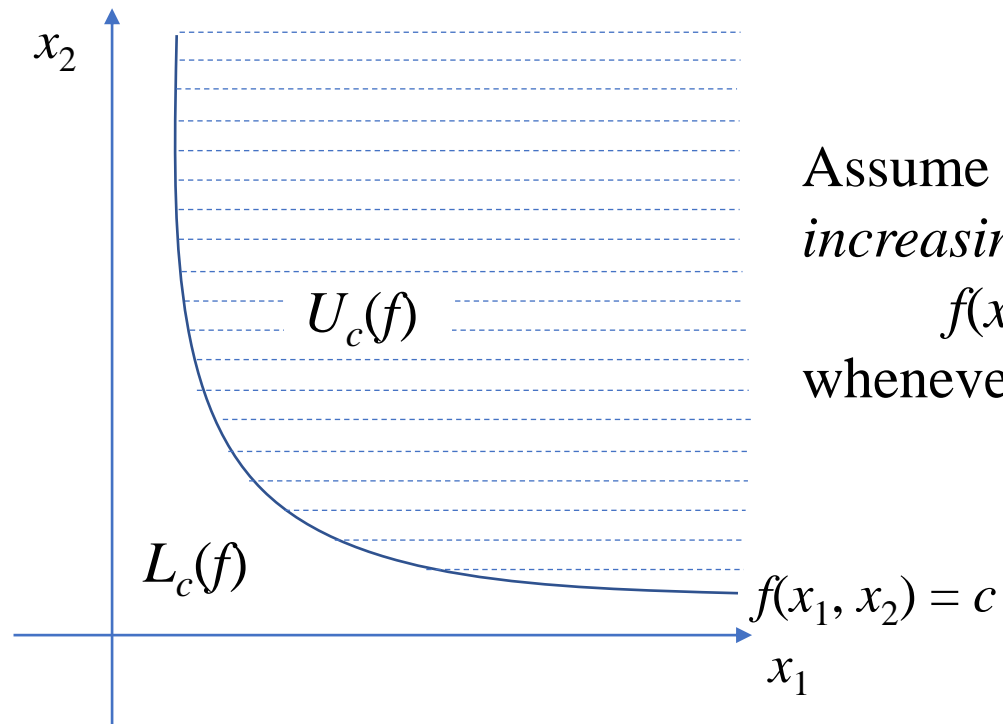
For any set  $X \subseteq \mathbb{R}^n$  and function  $f: X \rightarrow \mathbb{R}$ ,

- the ***upper-contour set*** of  $f$  for  $c \in \mathbb{R}$  is defined to be

$$U_c(f) = \{x \in X \mid f(x) \geq c\};$$

- the ***lower-contour set*** of  $f$  for  $c \in \mathbb{R}$  is defined to be

$$L_c(f) = \{x \in X \mid f(x) \leq c\}.$$



Assume that  $f$  is *monotonically increasing* in the sense that

$$f(x_1, x_2) \geq f(a_1, a_2)$$

whenever  $(x_1, x_2) \geq (a_1, a_2)$ .

**Theorem 7:** For any convex set  $X \subseteq \mathbb{R}^n$ , a function  $f: X \rightarrow \mathbb{R}$  is

- quasi-concave iff  $\forall c \in \mathbb{R}$ , the upper-contour set  $U_c(f)$  is convex;
- quasi-convex iff  $\forall c \in \mathbb{R}$ , the lower-contour set  $L_c(f)$  is convex.

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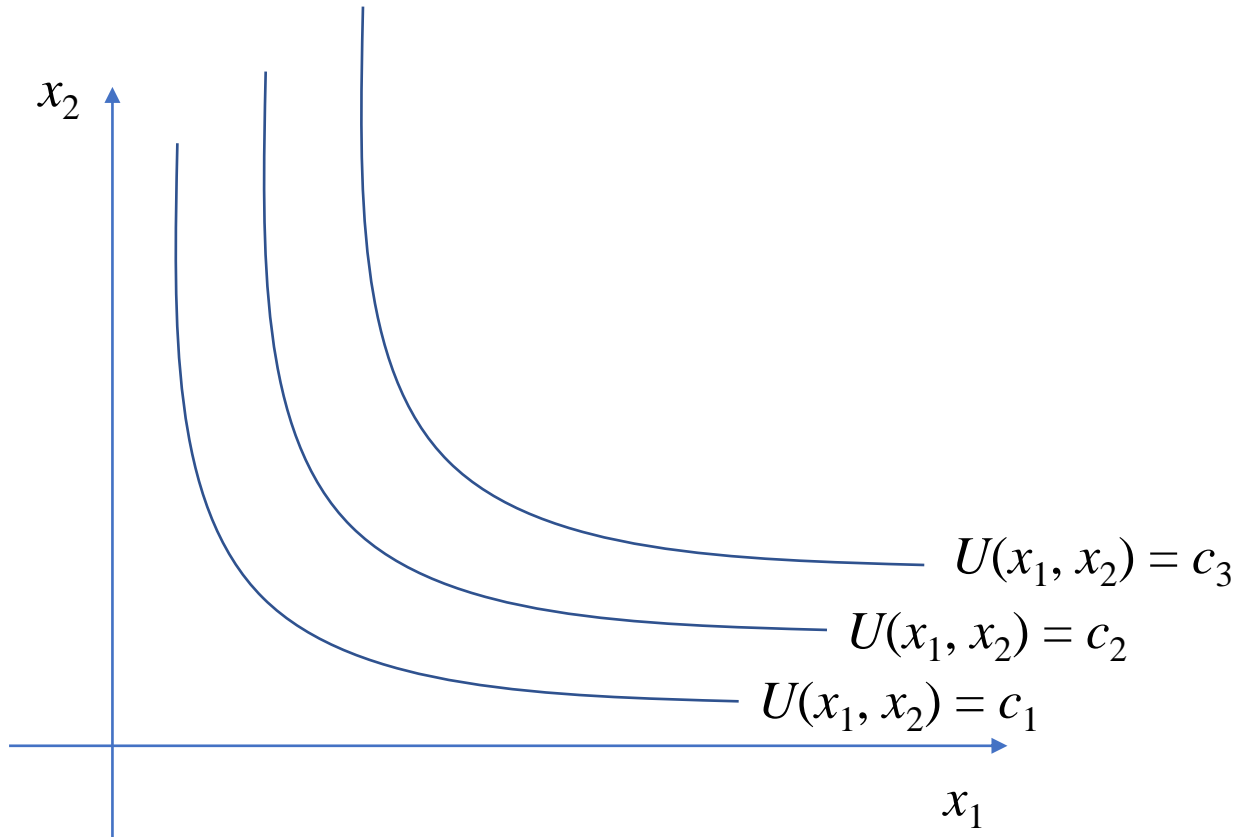
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- quasi-convex iff  $\forall c \in \mathbb{R}$ , the lower-contour set  $L_c(f)$  is convex.

- If  $f: X \rightarrow \mathbb{R}$  is quasi-concave, then  $\forall x, y \in X$  with  $f(x) \geq c$  and  $f(y) \geq c$ ,  $\forall \lambda \in [0, 1]$ ,  
$$f(\lambda x + (1-\lambda)y) \geq \min\{f(x), f(y)\} \geq c.$$
- On the other hand, suppose that  $\forall c \in \mathbb{R}$ ,  $\{x \in X \mid f(x) \geq c\}$  is convex. Note that  $\forall x, y \in X$ ,  $f(x) \geq \min\{f(x), f(y)\}$  and  $f(y) \geq \min\{f(x), f(y)\}$ , and hence  $\forall \lambda \in [0, 1]$ ,  $f(\lambda x + (1-\lambda)y) \geq \min\{f(x), f(y)\}$ .



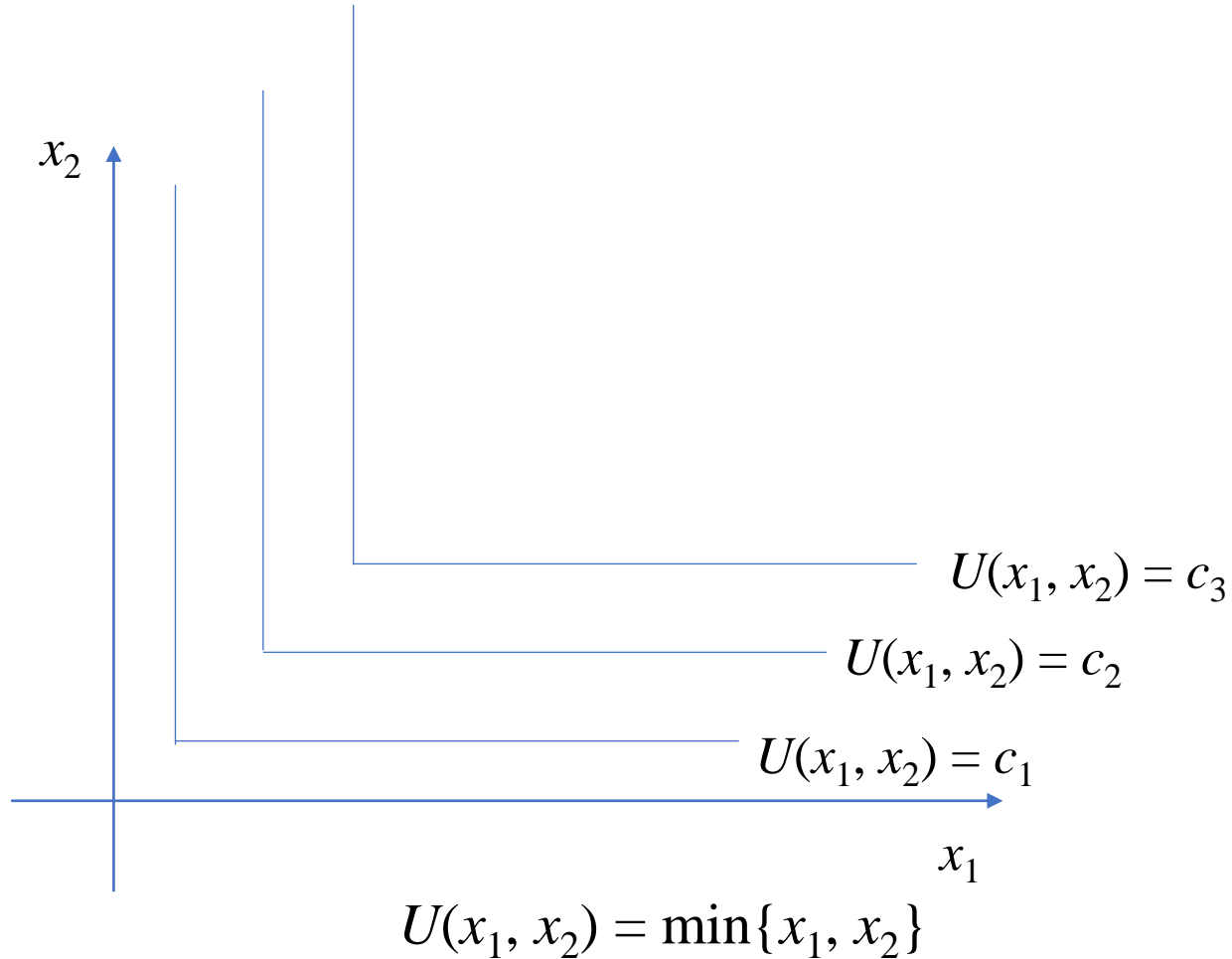
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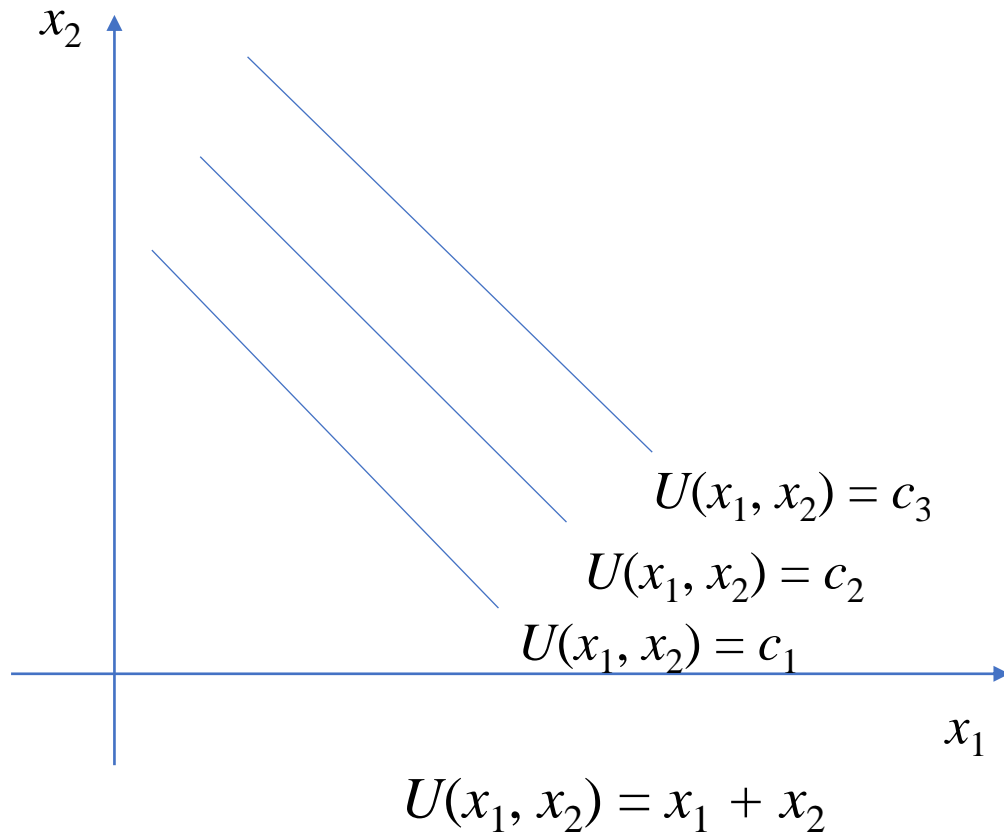
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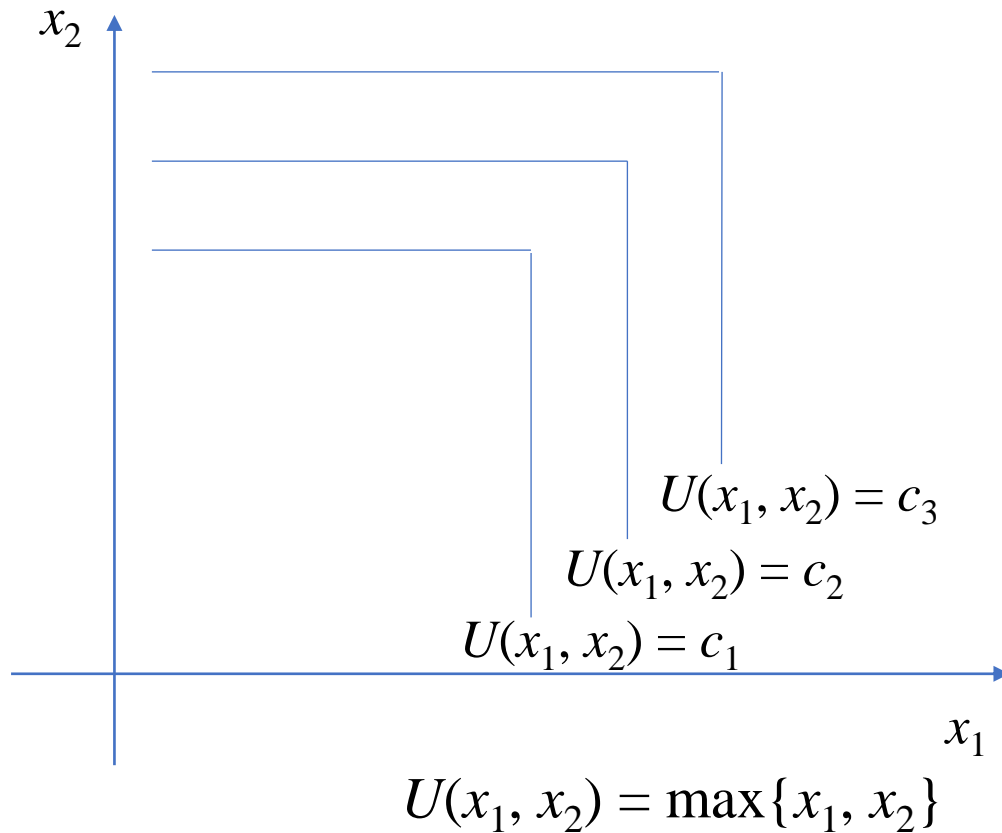
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**Theorem 8:** Let  $X \subseteq \mathbb{R}^n$  be open and convex and  $f: X \rightarrow \mathbb{R}$  continuously differentiable. Then  $f$  is

- quasi-concave iff  $Df(x) \cdot (y - x) \geq 0$  whenever  $f(y) \geq f(x)$  for all  $x, y \in X$ ;
- quasi-convex iff  $Df(x) \cdot (y - x) \leq 0$  whenever  $f(y) \leq f(x)$  for all  $x, y \in X$ ;
- strictly quasi-concave if  $Df(x) \cdot (y - x) > 0$  whenever  $f(y) \geq f(x)$  for all  $x, y \in X$  with  $x \neq y$ ;
- strictly quasi-convex if  $Df(x) \cdot (y - x) < 0$  whenever  $f(y) \leq f(x)$  for all  $x, y \in X$  with  $x \neq y$ .

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- strictly quasi-convex if  $Df(x) \cdot (y - x) < 0$  whenever  $f(y) \leq f(x)$  for all  $x, y \in X$  with  $x \neq y$ .

**Example:**  $f(x, y) = xy$ ,  $x > 0$ ,  $y > 0$ .

- Let  $f(x, y) \geq f(a, b)$ , i.e.,  $xy \geq ab$ . Then

$$\begin{aligned} Df(a, b) \cdot ((x, y) - (a, b)) &= (b, a) \cdot ((x, y) - (a, b)) \\ &= (b, a) \cdot (x - a, y - b) \\ &= b(x - a) + a(y - b) \\ &= bx + ay - 2ab \\ &\geq 2\sqrt{xyab} - 2ab \\ &\geq 2\sqrt{abab} - 2ab \\ &= 0. \end{aligned}$$

**Theorem 9:** Let  $X \subseteq \mathbb{R}^n$  be open and convex, and  $f: X \rightarrow \mathbb{R}$  twice continuously differentiable.

(i) If  $f$  is quasi-concave, then  $(-1)^k |\bar{H}_k(x)| \geq 0 \ \forall x \in X \ \forall k \in \{1, 2, \dots, n\}$ ;

(ii) If  $f$  is quasi-convex, then  $|\bar{H}_k(x)| \leq 0 \ \forall x \in X \ \forall k \in \{1, 2, \dots, n\}$ ;

(iii) If  $(-1)^k |\bar{H}_k(x)| > 0 \ \forall x \in X \ \forall k \in \{1, 2, \dots, n\}$ , then  $f$  is strictly quasi-concave;

(iv) If  $|\bar{H}_k(x)| < 0 \ \forall x \in X \ \forall k \in \{1, 2, \dots, n\}$ , then  $f$  is strictly quasi-convex.

$\forall x \in X, \forall k \in \{1, 2, \dots, n\}$ , let

$$\bar{H}_k(x) = \begin{pmatrix} 0 & \frac{\partial f}{\partial x_1} & \dots & \frac{\partial f}{\partial x_k} \\ \frac{\partial f}{\partial x_1} & \frac{\partial^2 f}{\partial x_1^2} & \dots & \frac{\partial^2 f}{\partial x_1 \partial x_k} \\ \dots & \dots & \dots & \dots \\ \frac{\partial f}{\partial x_k} & \frac{\partial^2 f}{\partial x_k \partial x_1} & \dots & \frac{\partial^2 f}{\partial x_k^2} \end{pmatrix}$$

and  $\bar{H}(x) = \bar{H}_n(x)$ .

**Theorem 9:** Let  $X \subseteq \mathbb{R}^n$  be open and convex, and  $f: X \rightarrow \mathbb{R}$  twice continuously differentiable.

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and  $\bar{H}(x) = \bar{H}_n(x)$ .

**Example:**  $f(x, y) = xy, x > 0, y > 0$ .

- $\bar{H}(x, y) = \begin{pmatrix} 0 & y & x \\ y & 0 & 1 \\ x & 1 & 0 \end{pmatrix}$ .
- $|\bar{H}_1(x, y)| = \begin{vmatrix} 0 & y \\ y & 0 \end{vmatrix} = -y^2 < 0, |\bar{H}_2(x, y)| = 2xy > 0$ .



**Theorem 10:** Let  $X \subseteq \mathbb{R}^n$  and  $A \subseteq \mathbb{R}$  be convex.

- (i) If  $f: X \rightarrow \mathbb{R}$  is quasi-concave and  $g: A \rightarrow \mathbb{R}$  increasing with  $f(X) \subseteq A$ , then  $g \circ f$  is quasi-concave; if  $f$  is quasi-concave and  $g$  decreasing, then  $g \circ f$  is quasi-convex;
- (ii) If  $f: X \rightarrow \mathbb{R}$  is quasi-convex and  $g: A \rightarrow \mathbb{R}$  increasing with  $f(X) \subseteq A$ , then  $g \circ f$  is quasi-convex; if  $f$  is quasi-convex and  $g$  decreasing, then  $g \circ f$  is quasi-concave;
- (iii) If  $f: X \rightarrow \mathbb{R}$  is strictly quasi-concave and  $g: A \rightarrow \mathbb{R}$  strictly increasing with  $f(X) \subseteq A$ , then  $g \circ f$  is strictly quasi-concave;
- (iv) If  $f: X \rightarrow \mathbb{R}$  is strictly quasi-convex and  $g: A \rightarrow \mathbb{R}$  strictly increasing with  $f(X) \subseteq A$ , then  $g \circ f$  is strictly quasi-convex;
- (v) If  $f: X \rightarrow \mathbb{R}$  is concave and  $g: A \rightarrow \mathbb{R}$  increasing and concave with  $f(X) \subseteq A$ , then  $g \circ f$  is concave;
- (vi) If  $f: X \rightarrow \mathbb{R}$  is convex and  $g: A \rightarrow \mathbb{R}$  increasing and convex with  $f(X) \subseteq A$ , then  $g \circ f$  is convex.

- See Exercises 1 and 3.

**Theorem 11:** Let  $X \subseteq \mathbb{R}^n$  be convex.

(i) *Nonnegative linear combination of concave functions must be concave*, i.e., for any concave functions  $f_1, f_2, \dots, f_n$  defined on  $X$ ,  $\forall a_1, a_2, \dots, a_n \in \mathbb{R}_+$ ,  $\sum_{k=1}^n a_k f_k$  is concave.

(ii) *Nonnegative linear combination of convex functions must be convex*, i.e., for any convex functions  $f_1, f_2, \dots, f_n$  defined on  $X$ ,  $\forall a_1, a_2, \dots, a_n \in \mathbb{R}_+$ ,  $\sum_{k=1}^n a_k f_k$  is convex.

- See Exercise 1.

**Theorem 12:** Let  $X \subseteq \mathbb{R}^n$  be nonempty and convex.

- A strictly concave function cannot be convex, and a strictly convex function cannot be concave (unless  $|X| = 1$ ).
- Let  $n = 1$ . If  $f: X \rightarrow \mathbb{R}$  is increasing or decreasing, then  $f$  is both quasi-concave and quasi-convex; if  $f$  is strictly increasing or strictly decreasing, then  $f$  is both strictly quasi-concave and strictly quasi-convex.

- See Exercise 1.

**Example 3:**

**(1)**  $f(x) = x, g(x) = -x, h(x) = x^3.$

**(2)**  $u(x, y) = x^a y^b, x > 0, y > 0, a > 0, b > 0.$

**(3)**  $f(x, y) = (x - 1)^2(y - 1)^2.$

**Example 3:**

(1)  $f(x) = x$ ,  $g(x) = -x$ ,  $h(x) = x^3$ .

(2)  $u(x, y) = x^a y^b$ ,  $x > 0$ ,  $y > 0$ ,  $a > 0$ ,  $b > 0$ .

(3)  $f(x, y) = (x - 1)^2(y - 1)^2$ .

(1)  $f$  and  $g$  are concave, convex, strictly quasi-concave, and strictly quasi-convex, but neither strictly concave nor strictly convex;  $h$  is strictly quasi-convex and strictly quasi-concave, but neither concave nor convex.

**Example 3:**

(1)  $f(x) = x$ ,  $g(x) = -x$ ,  $h(x) = x^3$ .

(2)  $u(x, y) = x^a y^b$ ,  $x > 0$ ,  $y > 0$ ,  $a > 0$ ,  $b > 0$ .

(3)  $f(x, y) = (x - 1)^2(y - 1)^2$ .

(2)  $u(x, y)$  is strictly quasi-concave since  $\bar{H}(x, y) =$

$$\begin{pmatrix} 0 & ax^{a-1}y^b & bx^ay^{b-1} \\ ax^{a-1}y^b & a(a-1)x^{a-2}y^b & abx^{a-1}y^{b-1} \\ bx^ay^{b-1} & abx^{a-1}y^{b-1} & b(b-1)x^ay^{b-2} \end{pmatrix},$$

$|\bar{H}_1(x, y)| = -a^2x^{2a-2}y^{2b} < 0,$

$|\bar{H}_2(x, y)| = (a + b)abx^{3a-2}y^{3b-2} > 0.$

### Example 3:

(1)  $f(x) = x, g(x) = -x, h(x) = x^3$ .

(2)  $u(x, y) = x^a y^b, x > 0, y > 0, a > 0, b > 0$ .

(3)  $f(x, y) = (x - 1)^2(y - 1)^2$ .

(3)  $\bar{H}(x, y) =$

$$\begin{pmatrix} 0 & 2(x-1)(y-1)^2 & 2(x-1)^2(y-1) \\ 2(x-1)(y-1)^2 & 2(y-1)^2 & 4(x-1)(y-1) \\ 2(x-1)^2(y-1) & 4(x-1)(y-1) & 2(x-1)^2 \end{pmatrix},$$

$$|\bar{H}_1(x, y)| = -4(x-1)^2(y-1)^4 \leq 0,$$

$$|\bar{H}_2(x, y)| = 16(x-1)^4(y-1)^4 \geq 0.$$

However,  $f(x, y)$  is not quasi-concave since

$$f(0.5(0, 0) + 0.5(2, 2)) = f(1, 1) = 0 < 1 = \min\{f(0, 0), f(2, 2)\}.$$

- Even if the domain is restricted to  $\mathbb{R}_{++}^2$ , we have

$$\begin{aligned} f(0.5(0.2, 0.2) + 0.5(1.8, 1.8)) &= f(1, 1) = 0 \\ &< 0.64^2 = \min\{f(0.2, 0.2), f(1.8, 1.8)\}. \end{aligned}$$

# Convex Preference Relations

Let  $X \subseteq \mathbb{R}^n$  be a set of alternatives and  $\succeq$  a rational preference relation on  $X$ . We say that  $\succeq$  is

- **convex** if  $\forall x \in X$ ,  $\{y \in X \mid y \succeq x\}$  is convex; i.e.,  $\forall x, y, z \in X$ , if  $y \succeq x$  and  $z \succeq x$ , then  $\forall t \in [0, 1]$ ,  $ty + (1-t)z \succeq x$ ;
- **strictly convex** if  $\forall x, y, z \in X$  such that  $y \succeq x$ ,  $z \succeq x$ , and  $y \neq z$ , we have  $ty + (1-t)z \succ x \forall t \in (0, 1)$ .
- **weakly convex** if  $\forall x, y \in X$  with  $x \succ y$ , we have  $tx + (1-t)y \succ y \forall t \in (0, 1)$ .
- **explicitly convex** if it is both convex and weakly convex.
- **weakly monotone** if  $\forall x, y \in X$ ,  $x > y$  implies  $x \succeq y$ ;
- **monotone** if  $\forall x, y \in X$ ,  $x \geq y$  implies  $x \succeq y$ ;
- **strictly monotone** if  $\forall x, y \in X$ ,  $x > y$  implies  $x \succ y$ ;
- **strongly monotone** if  $\forall x, y \in X$ ,  $x \geq y$  and  $x \neq y$  imply  $x \succ y$ .



**Theorem 13:** Let  $X \subseteq \mathbb{R}^n$  be convex. If  $\succsim$  is represented by a utility function  $u: X \rightarrow \mathbb{R}$ , then

- $\succsim$  is convex iff  $u$  is quasi-concave,
- $\succsim$  is strictly convex iff  $u$  is strictly quasi-concave.

- See Exercise 1.

## Homogenous and Homothetic Functions:

Let  $X \subseteq \mathbb{R}^n$  be a cone. For any  $k \in \mathbb{R}$ , we say that

- $f: X \rightarrow \mathbb{R}$  is **homogeneous** of degree  $k$  if for any  $x \in X$  and  $r > 0$ ,  $f(rx) = r^k f(x)$ ;
- $h: X \rightarrow \mathbb{R}$  is **homothetic** if  $h$  is a strictly increasing transformation of a homogeneous function; that is,  $h = g \circ f$ , where  $g: f(X) \rightarrow \mathbb{R}$  is strictly increasing and  $f: X \rightarrow \mathbb{R}$  homogeneous of degree  $k$ .
- **Example:** The utility function  $v(x, y) = x^3 y^3 + e^{xy} + 10$  is homothetic, since the utility function  $u(x, y) = xy$  is homogeneous of degree 2 and  $g(z) = z^3 + e^z + 10$  is an increasing transformation. Note that  $u$  and  $v$  represent the same preference.

- A set  $X \subseteq \mathbb{R}^n$  is a **cone** if  $\forall x \in X$ ,  $\forall r > 0$ ,  $rx \in X$ .

**Theorem 14:** Let  $X \subseteq \mathbb{R}^n$  be a convex cone. If  $f: X \rightarrow \mathbb{R}$  is quasi-concave and homogenous of degree  $k \in (0, 1]$  such that  $f(0) = 0$  (if  $0 \in X$ ) and  $f(x) > 0 \forall x \in X \setminus \{0\}$ , then  $f$  is concave.

- See Exercise 1.

## **Example 4:**

### **(1) The Cobb-Douglas Utility Function:**

$$u(x_1, \dots, x_n) = a \prod_{i=1}^n x_i^{b_i},$$

where  $x_1, \dots, x_n, a, b_1, \dots, b_n > 0$ .

### **(2) The Generalized CES (Constant Elasticity of Substitution) Utility Function:**

$$u(x_1, \dots, x_n) = a \left( \sum_{i=1}^n b_i x_i^{-\rho} \right)^{-\frac{c}{\rho}},$$

where  $x_1, \dots, x_n, a, b_1, \dots, b_n, c > 0$ , and  $\rho \neq 0$ .

## Example 4:

### (1) The Cobb-Douglas Utility Function:

$$u(x_1, \dots, x_n) = a \prod_{i=1}^n x_i^{b_i},$$

where  $x_1, \dots, x_n, a, b_1, \dots, b_n > 0$ .

$$H(x) = u(x) \begin{pmatrix} \frac{b_1(b_1-1)}{x_1^2} & \frac{b_1 b_2}{x_1 x_2} & \dots & \frac{b_1 b_n}{x_1 x_n} \\ \frac{b_1 b_2}{x_1 x_2} & \frac{b_2(b_2-1)}{x_2^2} & \dots & \frac{b_2 b_n}{x_2 x_n} \\ \dots & \dots & \dots & \dots \\ \frac{b_1 b_n}{x_1 x_n} & \frac{b_2 b_n}{x_2 x_n} & \dots & \frac{b_n(b_n-1)}{x_n^2} \end{pmatrix}.$$

$\forall k = 1, 2, \dots, n$ , let  $s_k = \sum_{i=1}^k b_i$ , and then  $|H_k(x)| =$

$$(u(x))^k \frac{b_1 b_2 \dots b_k}{(x_1 x_2 \dots x_k)^2} \begin{vmatrix} b_1 - 1 & b_1 & \dots & b_1 \\ b_2 & b_2 - 1 & \dots & b_2 \\ \dots & \dots & \dots & \dots \\ b_k & b_k & \dots & b_k - 1 \end{vmatrix} =$$

$$(u(x))^k \frac{b_1 b_2 \dots b_k}{(x_1 x_2 \dots x_k)^2} \begin{vmatrix} s_k - 1 & s_k - 1 & \dots & s_k - 1 \\ b_2 & b_2 - 1 & \dots & b_2 \\ \dots & \dots & \dots & \dots \\ b_k & b_k & \dots & b_k - 1 \end{vmatrix} =$$

$$(u(x))^k \frac{b_1 b_2 \dots b_k (s_k - 1)}{(x_1 x_2 \dots x_k)^2} \begin{vmatrix} 1 & 1 & \dots & 1 \\ b_2 & b_2 - 1 & \dots & b_2 \\ \dots & \dots & \dots & \dots \\ b_k & b_k & \dots & b_k - 1 \end{vmatrix} =$$

### Example 4:

#### (1) The Cobb-Douglas Utility Function:

$$u(x_1, \dots, x_n) = a \prod_{i=1}^n x_i^{b_i},$$

where  $x_1, \dots, x_n, a, b_1, \dots, b_n > 0$ .

$$H(x) = u(x) \begin{pmatrix} \frac{b_1(b_1-1)}{x_1^2} & \frac{b_1 b_2}{x_1 x_2} & \dots & \frac{b_1 b_n}{x_1 x_n} \\ \frac{b_1 b_2}{x_1 x_2} & \frac{b_2(b_2-1)}{x_2^2} & \dots & \frac{b_2 b_n}{x_2 x_n} \\ \dots & \dots & \dots & \dots \\ \frac{b_1 b_n}{x_1 x_n} & \frac{b_2 b_n}{x_2 x_n} & \dots & \frac{b_n(b_n-1)}{x_n^2} \end{pmatrix}.$$

$\forall k = 1, 2, \dots, n$ , let  $s_k = \sum_{i=1}^k b_i$ , and then  $|H_k(x)| =$

$$(u(x))^k \frac{b_1 b_2 \dots b_k}{(x_1 x_2 \dots x_k)^2} \begin{vmatrix} b_1 - 1 & b_1 & \dots & b_1 \\ b_2 & b_2 - 1 & \dots & b_2 \\ \dots & \dots & \dots & \dots \\ b_k & b_k & \dots & b_k - 1 \end{vmatrix} =$$

$$(u(x))^k \frac{b_1 b_2 \dots b_k (s_k - 1)}{(x_1 x_2 \dots x_k)^2} \begin{vmatrix} 1 & 0 & \dots & 0 \\ b_2 & -1 & \dots & 0 \\ \dots & \dots & \dots & \dots \\ b_k & 0 & \dots & -1 \end{vmatrix} =$$

$$(-1)^{k-1} (s_k - 1) (u(x))^k \frac{b_1 b_2 \dots b_k}{(x_1 x_2 \dots x_k)^2},$$

having the same sign as  $(-1)^k$  if  $\sum_{i=1}^n b_i < 1$ .  
Hence  $u$  is strictly concave if  $\sum_{i=1}^n b_i < 1$ .

## Example 4:

### (1) The Cobb-Douglas Utility Function:

$$u(x_1, \dots, x_n) = a \prod_{i=1}^n x_i^{b_i},$$

where  $x_1, \dots, x_n, a, b_1, \dots, b_n > 0$ .

- $u$  is strictly concave if  $\sum_{i=1}^n b_i < 1$ , and not concave if  $\sum_{i=1}^n b_i > 1$ .
- Note that  $\ln u(x) = \ln a + \sum_{i=1}^n b_i \ln x_i$ , which is strictly concave since

$$D^2(\ln u(x)) = \begin{pmatrix} -\frac{b_1}{x_1^2} & 0 & \dots & 0 \\ 0 & -\frac{b_2}{x_2^2} & \dots & 0 \\ \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & -\frac{b_n}{x_n^2} \end{pmatrix}$$

is negative definite. Hence  $u(x) = e^{\ln u(x)}$  is strictly quasi-concave.

## Example 4:

### (1) The Cobb-Douglas Utility Function:

$$u(x_1, \dots, x_n) = a \prod_{i=1}^n x_i^{b_i},$$

where  $x_1, \dots, x_n, a, b_1, \dots, b_n > 0$ .

- $u$  is strictly concave if  $\sum_{i=1}^n b_i < 1$ , and not concave if  $\sum_{i=1}^n b_i > 1$ .
- $u$  is strictly quasi-concave.
- When  $\sum_{i=1}^n b_i = 1$ , note that  $u$  is quasi-concave and homogeneous with degree 1 s.t.  $u(x) > 0$  for all  $x \in \mathbb{R}_{++}^n$ , implying that  $u$  is concave.



### Example 4:

#### (2) The Generalized CES (Constant Elasticity of Substitution) Utility Function:

$$u(x_1, \dots, x_n) = a \left( \sum_{i=1}^n b_i x_i^{-\rho} \right)^{-\frac{c}{\rho}},$$

where  $x_1, \dots, x_n, a, b_1, \dots, b_n, c > 0$ , and  $\rho \neq 0$ .

- Let  $v = \sum_{i=1}^n b_i x_i^{-\rho}$ , then  $u = av^{-\frac{c}{\rho}}$ .
- If  $\rho \leq -1$ , then  $v$  is quasi-convex (Indeed,  $v$  is convex) and  $u$  increasing in  $v$ . Thus  $u$  is quasi-convex.
- If  $-1 \leq \rho < 0$ , then  $v$  is quasi-concave (Indeed,  $v$  is concave) and  $u$  increasing in  $v$ . Thus  $u$  is quasi-concave.
- If  $\rho > 0$ , then  $v$  is quasi-convex (Indeed,  $v$  is convex) and  $u$  decreasing in  $v$ . Thus  $u$  is quasi-concave.

- If  $\rho = -1$ , then  $v$  is linear.
- Note that  $D^2(v(x)) =$

$$\begin{pmatrix} \frac{b_1 \rho(\rho+1)}{x_1^{\rho+2}} & 0 & \dots & 0 \\ 0 & \frac{b_2 \rho(\rho+1)}{x_2^{\rho+2}} & \dots & 0 \\ \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & \frac{b_n \rho(\rho+1)}{x_n^{\rho+2}} \end{pmatrix}.$$

**Theorem 15:** Let  $X \subseteq \mathbb{R}^n$  be a cone. If  $f: X \rightarrow \mathbb{R}$  is differentiable and homogeneous of degree  $k$ , then  $\forall i \in \{1, 2, \dots, n\}$ , the partial derivative function  $\partial f / \partial x_i$  is homogenous of degree  $k - 1$ .

**Theorem 15:** Let  $X \subseteq \mathbb{R}^n$  be a cone. If  $f: X \rightarrow \mathbb{R}$  is differentiable and homogeneous of degree  $k$ , then  $\forall i \in \{1, 2, \dots, n\}$ , the partial derivative function  $\partial f / \partial x_i$  is homogenous of degree  $k - 1$ .

- Differentiating  $f(rx^*) = r^k f(x^*)$  with respect to  $x_i^*$ , we have

$$r \frac{\partial f(rx^*)}{\partial x_i} = r^k \frac{\partial f(x^*)}{\partial x_i},$$

i.e.,

$$\frac{\partial f(rx^*)}{\partial x_i} = r^{k-1} \frac{\partial f(x^*)}{\partial x_i}.$$

**Theorem 16 (Euler's Formula):** Let  $X \subseteq \mathbb{R}^n$  be a cone. If  $f: X \rightarrow \mathbb{R}$  is differentiable and homogeneous of degree  $k$ , then  $\forall x^* \in X$ ,

$$kf(x^*) = \sum_{i=1}^n \frac{\partial f(x^*)}{\partial x_i} x_i^* .$$

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- Differentiating  $f(rx^*) = r^k f(x^*)$  with respect to  $r$ , we have

$$\sum_{i=1}^n \frac{\partial f(rx^*)}{\partial x_i} x_i^* = kr^{k-1} f(x^*),$$

and let  $r = 1$ .

**Theorem 16 (Euler's Formula):** Let  $X \subseteq \mathbb{R}^n$  be a cone. If  $f: X \rightarrow \mathbb{R}$  is differentiable and homogeneous of degree  $k$ , then  $\forall x^* \in X$ ,

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and let  $r = 1$ .

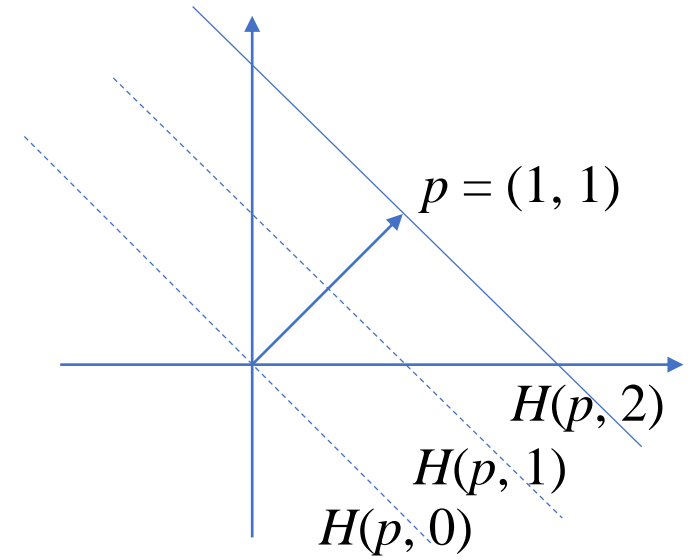
- **Example:** Let the production function  $F(K, L)$  be differentiable and homogeneous of degree 1, then

$$F(K, L) = \frac{\partial F(K,L)}{\partial K} K + \frac{\partial F(K,L)}{\partial L} L.$$

# Supporting and Separating Hyperplanes

Let  $c \in \mathbb{R}$  and  $p \in \mathbb{R}^n \setminus \{0\}$ .

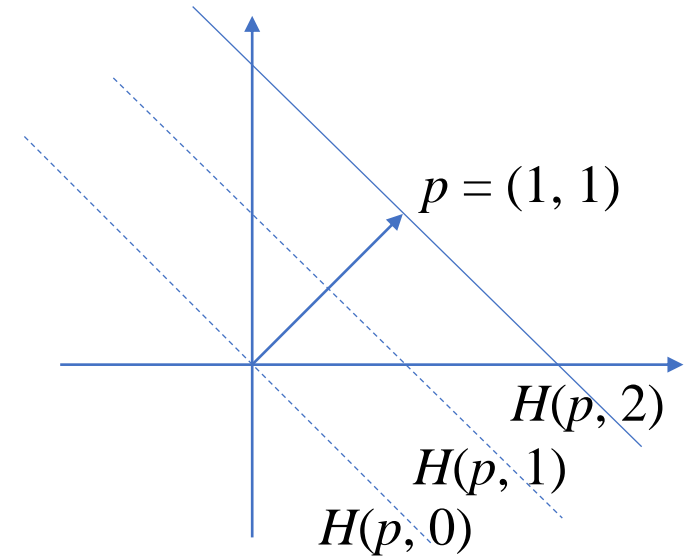
- The set  $H(p, c) = \{x \in \mathbb{R}^n \mid p \cdot x = c\}$  is a *hyperplane* in  $\mathbb{R}^n$  determined by  $(p, c)$ , where  $p$  is called the *normal vector* to the hyperplane  $H(p, c)$ .
- **Example:** Let  $p = (1, 1)$  and  $c = 2$ . Then
$$H(p, c) = \{(x_1, x_2) \in \mathbb{R}^2 \mid x_1 + x_2 = 2\}.$$



# Supporting and Separating Hyperplanes

Let  $c \in \mathbb{R}$  and  $p \in \mathbb{R}^n \setminus \{0\}$ .

- The set  $H(p, c) = \{x \in \mathbb{R}^n \mid p \cdot x = c\}$  is a **hyperplane** in  $\mathbb{R}^n$  determined by  $(p, c)$ , where  $p$  is called the **normal vector** to the hyperplane  $H(p, c)$ .
- **Example:** Let  $p = (1, 1)$  and  $c = 2$ . Then
$$H(p, c) = \{(x_1, x_2) \in \mathbb{R}^2 \mid x_1 + x_2 = 2\}.$$
- A **closed half-space** determined by  $H(p, c)$  is either the set  $\{x \in \mathbb{R}^n \mid p \cdot x \leq c\}$  or the set  $\{x \in \mathbb{R}^n \mid p \cdot x \geq c\}$ .
- An **open half-space** determined by  $H(p, c)$  is either the set  $\{x \in \mathbb{R}^n \mid p \cdot x < c\}$  or the set  $\{x \in \mathbb{R}^n \mid p \cdot x > c\}$ .

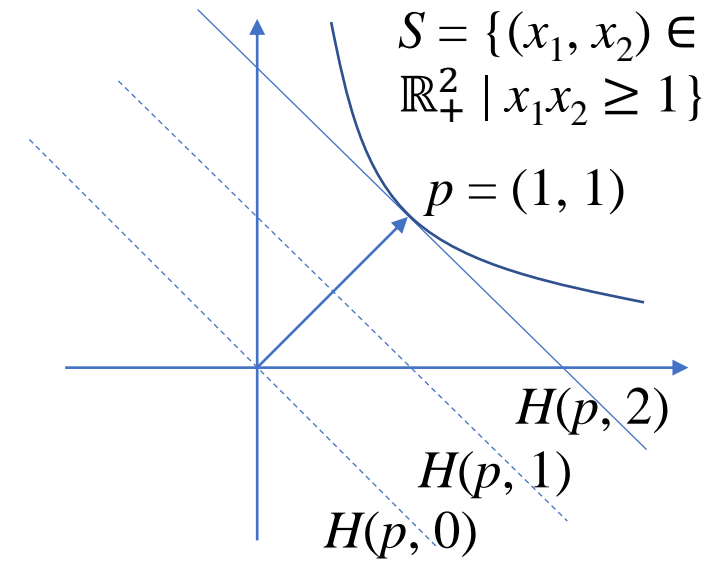




# Supporting and Separating Hyperplanes

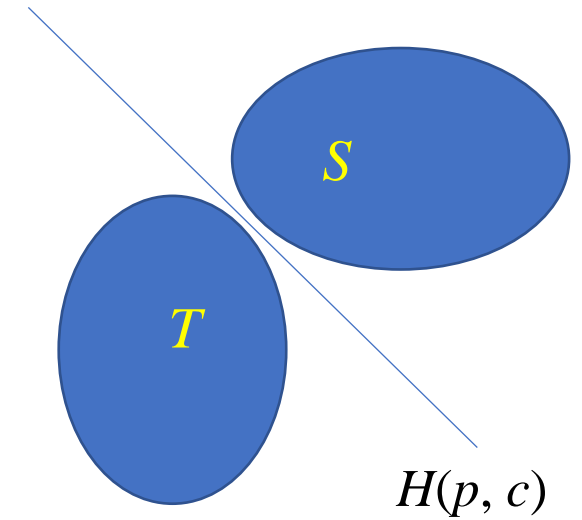
Let  $c \in \mathbb{R}$  and  $p \in \mathbb{R}^n \setminus \{0\}$ .

- The set  $H(p, c) = \{x \in \mathbb{R}^n \mid p \cdot x = c\}$  is a **hyperplane** in  $\mathbb{R}^n$  determined by  $(p, c)$ , where  $p$  is called the **normal vector** to the hyperplane  $H(p, c)$ .
- **Example:** Let  $p = (1, 1)$  and  $c = 2$ . Then
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- An **open half-space** determined by  $H(p, c)$  is either the set  $\{x \in \mathbb{R}^n \mid p \cdot x < c\}$  or the set  $\{x \in \mathbb{R}^n \mid p \cdot x > c\}$ .
- A **bounding hyperplane**  $H(p, c)$  to a set  $S \subseteq \mathbb{R}^n$  is a hyperplane such that  $S \subseteq \{x \in \mathbb{R}^n \mid p \cdot x \leq c\}$  or  $S \subseteq \{x \in \mathbb{R}^n \mid p \cdot x \geq c\}$ , i.e.,  $S$  lies entirely on one side of  $H(p, c)$ .
- A **supporting hyperplane**  $H(p, c)$  for a set  $S \subseteq \mathbb{R}^n$  is a bounding hyperplane to  $S$  that shares a point in common with the boundary of  $S$ .



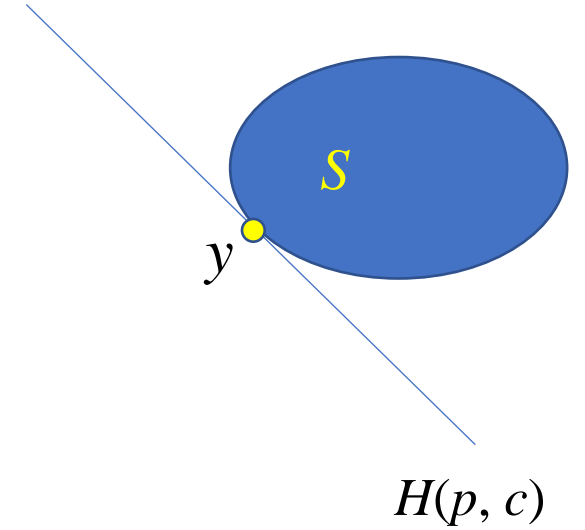
Let  $c \in \mathbb{R}$  and  $p \in \mathbb{R}^n \setminus \{0\}$ .

- The set  $H(p, c) = \{x \in \mathbb{R}^n \mid p \cdot x = c\}$  is a **hyperplane** in  $\mathbb{R}^n$  determined by  $(p, c)$ , where  $p$  is called the **normal vector** to the hyperplane  $H(p, c)$ .
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- A **supporting hyperplane**  $H(p, c)$  for a set  $S \subseteq \mathbb{R}^n$  is a bounding hyperplane to  $S$  that shares a point in common with the boundary of  $S$ .
- A hyperplane  $H(p, c)$  **separates** two sets  $S, T \subseteq \mathbb{R}^n$  if  $p \cdot s \leq c$  for all  $s \in S$  and  $p \cdot t \geq c$  for all  $t \in T$ , i.e.,  $S$  and  $T$  lie on opposite sides of  $H(p, c)$ .



# Supporting and Separating Hyperplanes

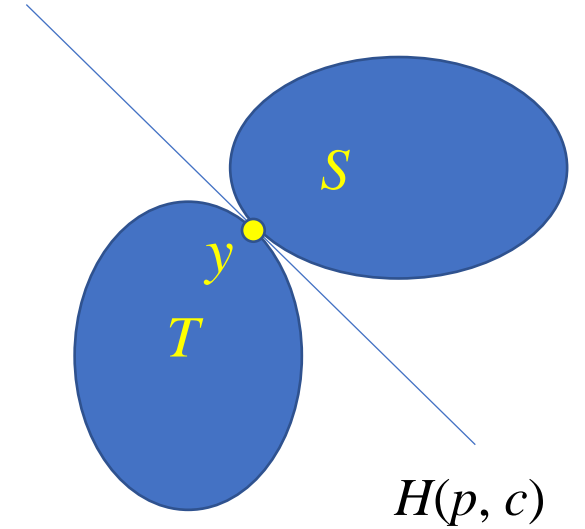
**The Supporting Hyperplane Theorem:** If  $S \subseteq \mathbb{R}^n$  is convex and  $y \in \partial S$ , then there exists a supporting hyperplane for  $S$  that passes through  $y$ .



# Supporting and Separating Hyperplanes

**The Supporting Hyperplane Theorem:** If  $S \subseteq \mathbb{R}^n$  is convex and  $y \in \partial S$ , then there exists a supporting hyperplane for  $S$  that passes through  $y$ .

**Minkowski's Separating Hyperplane Theorem:** For any two convex sets  $S, T \subseteq \mathbb{R}^n$ , if  $\text{Int}(S) \cap \text{Int}(T) = \emptyset$ , then there exists a hyperplane separating  $S$  and  $T$ .



# Exercise 1

- (1) Prove Theorem 10.
- (2) Prove Theorem 11.
- (3) Prove Theorem 12.
- (4) Prove Theorem 13.
- (5) **(Optional)** Prove Theorem 14.
- (6) Determine if the following functions are quasi-concave:
  - (a)  $f(x) = -\frac{x^2}{1+x^2}$ ;
  - (b)  $f(x, y) = ye^x, y > 0$ ;
  - (c)  $f(x_1, \dots, x_n) = \sum_{k=1}^n a_k x_k^b$ , where  $x_1, \dots, x_n, a_1, \dots, a_n, b > 0$ ;
  - (d)  $f(x) = 1 + x^2 + x^3$  if  $x < 0$ ,  $f(x) = 1$  if  $x \geq 0$ .
- (7) Show that the sum of two quasi-concave functions is not necessarily quasi-concave.

## Exercise 2 (Jensen's Inequality)

(1) For any nonempty convex set  $X \subseteq \mathbb{R}^n$ , show that a function  $f: X \rightarrow \mathbb{R}$  is

- concave iff  $f(\sum_{k=1}^m \lambda_k x_k) \geq \sum_{k=1}^m \lambda_k f(x_k)$  for all  $x_1, \dots, x_m \in X$  and  $\lambda_1, \dots, \lambda_m \in [0, 1]$  with  $\sum_{k=1}^m \lambda_k = 1$ ;
- convex iff  $f(\sum_{k=1}^m \lambda_k x_k) \leq \sum_{k=1}^m \lambda_k f(x_k)$  for all  $x_1, \dots, x_m \in X$  and  $\lambda_1, \dots, \lambda_m \in [0, 1]$  with  $\sum_{k=1}^m \lambda_k = 1$ .

(2) (Optional) Let  $\phi: [a, b] \rightarrow \mathbb{R}$  and  $\lambda: [a, b] \rightarrow \mathbb{R}_+$  be continuous and  $\int_a^b \lambda(t) dt = 1$ . Show that if  $f$  is a concave function defined on the range of  $\phi$ , then

$$f(\int_a^b \lambda(t) \phi(t) dt) \geq \int_a^b \lambda(t) f(\phi(t)) dt.$$

## Exercise 3

(1) Let  $X \subseteq \mathbb{R}^n$  and  $A \subseteq \mathbb{R}$  be convex. Show that:

(i) If  $f: X \rightarrow \mathbb{R}$  is concave and  $g: A \rightarrow \mathbb{R}$  decreasing and convex with  $f(X) \subseteq A$ , then  $g \circ f$  is convex;

(ii) If  $f: X \rightarrow \mathbb{R}$  is convex and  $g: A \rightarrow \mathbb{R}$  decreasing and concave with  $f(X) \subseteq A$ , then  $g \circ f$  is concave;

(iii) If  $f: X \rightarrow \mathbb{R}$  is strictly concave and  $g: A \rightarrow \mathbb{R}$  strictly increasing and concave with  $f(X) \subseteq A$ , then  $g \circ f$  is strictly concave;

(iv) If  $f: X \rightarrow \mathbb{R}$  is strictly convex and  $g: A \rightarrow \mathbb{R}$  strictly increasing and convex with  $f(X) \subseteq A$ , then  $g \circ f$  is strictly convex;

(v) If  $f: X \rightarrow \mathbb{R}$  is strictly quasi-concave and  $g: A \rightarrow \mathbb{R}$  strictly decreasing with  $f(X) \subseteq A$ , then  $g \circ f$  is strictly quasi-convex;

(vi) If  $f: X \rightarrow \mathbb{R}$  is strictly quasi-convex and  $g: A \rightarrow \mathbb{R}$  strictly decreasing with  $f(X) \subseteq A$ , then  $g \circ f$  is strictly quasi-concave.

(2) Can a strictly concave function be strictly quasi-convex? Can a strictly convex function be strictly quasi-concave?

## Exercise 4

Let  $X \subseteq \mathbb{R}_{++}^n$  be open and  $f: X \rightarrow \mathbb{R}$  differentiable at  $x \in X$  with  $f(x) \neq 0$ .

The *partial elasticity* of  $f$  with respect to  $x_i$  is defined by

$$\text{El}_{x_i}(f(x)) = \frac{x_i}{f(x)} \frac{\partial f(x)}{\partial x_i} = \frac{\partial \ln |f(x)|}{\partial \ln x_i}.$$

The *marginal rate of substitution* of  $x_j$  for  $x_i$  is defined by

$$\text{MRS}_{x_j, x_i} = \frac{\frac{\partial f(x)}{\partial x_i}}{\frac{\partial f(x)}{\partial x_j}}.$$

The *elasticity of substitution* of  $x_j$  for  $x_i$  ( $i \neq j$ ) is defined by

$$\sigma_{x_j, x_i} = \text{El}_{\text{MRS}_{x_j, x_i}} \left( \frac{x_j}{x_i} \right) = \frac{\partial \ln \frac{x_j}{x_i}}{\partial \ln |\text{MRS}_{x_j, x_i}|}.$$

- Let  $f(x) = a \left( \sum_{i=1}^n b_i x_i^{-\rho} \right)^{-\frac{c}{\rho}}$ ,  $a, b_1, \dots, b_n, c > 0$ ,  $\rho > -1$ , and  $\rho \neq 0$ . Find  $\text{MRS}_{x_j, x_i}$  and  $\sigma_{x_j, x_i}$  for each  $i \neq j \in \{1, 2, \dots, n\}$ .



## Exercise 5 (L'Hospital's Rule)

(1) (Optional) Let  $X \subseteq \mathbb{R}$  and  $f: X \rightarrow \mathbb{R}$  and  $g: X \rightarrow \mathbb{R}$  be differentiable in some  $(a, b) \subseteq X$ ,  $-\infty \leq a < b \leq \infty$ , and  $g'(x) \neq 0 \forall x \in (a, b)$ .

- Suppose that  $\lim_{x \rightarrow a} \frac{f'(x)}{g'(x)} = c \in \overline{\mathbb{R}}$ . Show that if  $\lim_{x \rightarrow a} f(x) = \lim_{x \rightarrow a} g(x) = 0$ , or if  $\lim_{x \rightarrow a} |g(x)| = \infty$ , then  $\lim_{x \rightarrow a} \frac{f(x)}{g(x)} = c$ .
- Suppose that  $\lim_{x \rightarrow b} \frac{f'(x)}{g'(x)} = d \in \overline{\mathbb{R}}$ . Show that if  $\lim_{x \rightarrow b} f(x) = \lim_{x \rightarrow b} g(x) = 0$ , or if  $\lim_{x \rightarrow b} |g(x)| = \infty$ , then  $\lim_{x \rightarrow b} \frac{f(x)}{g(x)} = d$ .

(2) Let  $f(x) = x + \cos(x)\sin(x)$  and  $g(x) = e^{\sin(x)}(x + \cos(x)\sin(x))$ . Show that  $\lim_{x \rightarrow \infty} \frac{f'(x)}{g'(x)} = 0$  but  $\lim_{x \rightarrow \infty} \frac{f(x)}{g(x)}$  does not exist.

(3) Let  $X \subseteq \mathbb{R}_{++}^n$  and  $f: X \rightarrow \mathbb{R}$  be defined by  $f(x) = a \left( \sum_{i=1}^n b_i x_i^{-\rho} \right)^{-\frac{c}{\rho}}$ , where  $a, b_1, \dots, b_n, c > 0$ , and  $\rho \neq 0$ . Find

- $\lim_{\rho \rightarrow 0} a \left( \sum_{i=1}^n b_i x_i^{-\rho} \right)^{-\frac{c}{\rho}}$  when  $\sum_{i=1}^n b_i = 1$ ;
- $\lim_{\rho \rightarrow \infty} a \left( \sum_{i=1}^n b_i x_i^{-\rho} \right)^{-\frac{c}{\rho}}$ .

Thank you!