

# Math Review

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The material contained in these slides draws heavily on:  
Geoffrey A. Jehle and Philip J. Reny (2011). *Advanced Microeconomic  
Theory* (3rd Edition). Prentice Hall, 672 p.

# Basic definitions

A **set** is any collection of elements. Sets can be defined by *enumeration* of their elements, e.g.,  $S = \{2, 4, 6, 8\}$ , or by *description* of their elements, e.g.,  $S = \{x \mid x \text{ is a positive even integer greater than zero and less than } 10\}$ . When we wish to denote membership or inclusion in a set, we use the symbol  $\in$ . For example, if  $S = \{2, 5, 7\}$ , we say that  $5 \in S$ .

A set  $S$  is a **subset** of another set  $T$  if every element of  $S$  is also an element of  $T$ . We write  $S \subset T$  ( $S$  is contained in  $T$ ) or  $T \supset S$  ( $T$  contains  $S$ ). If  $S \subset T$ , then  $x \in S \Rightarrow x \in T$ .

Two sets are **equal sets** if they each contain exactly the same elements. We write  $S = T$  whenever  $x \in S \Rightarrow x \in T$  and  $x \in T \Rightarrow x \in S$ . Thus,  $S$  and  $T$  are equal sets if and only if  $S \subset T$  and  $T \subset S$ . For example, if  $S = \{\text{integers, } x \mid x^2 = 1\}$  and  $T = \{-1, 1\}$ , then  $S = T$ .

A set  $S$  is **empty** or is an **empty set** if it contains no elements at all. For example, if  $A = \{x \mid x^2 = 0 \text{ and } x > 1\}$ , then  $A$  is empty. We denote the empty set by the symbol  $\emptyset$  and write  $A = \emptyset$ .

$n$ -space is defined as the set product

$$\mathbb{R}^n \equiv \underbrace{\mathbb{R} \times \mathbb{R} \times \dots \times \mathbb{R}}_{n \text{ times}} \equiv \{(x_1, \dots, x_n) \mid x_i \in \mathbb{R}, i = 1, \dots, n\}.$$

# Convex Sets

## **Convex Sets in $\mathbb{R}^n$**

*$S \subset \mathbb{R}^n$  is a convex set if for all  $\mathbf{x}^1 \in S$  and  $\mathbf{x}^2 \in S$ , we have*

$$t\mathbf{x}^1 + (1 - t)\mathbf{x}^2 \in S$$

*for all  $t$  in the interval  $0 \leq t \leq 1$ .*

## **The Intersection of Convex Sets is Convex**

*Let  $S$  and  $T$  be convex sets in  $\mathbb{R}^n$ . Then  $S \cap T$  is a convex set.*

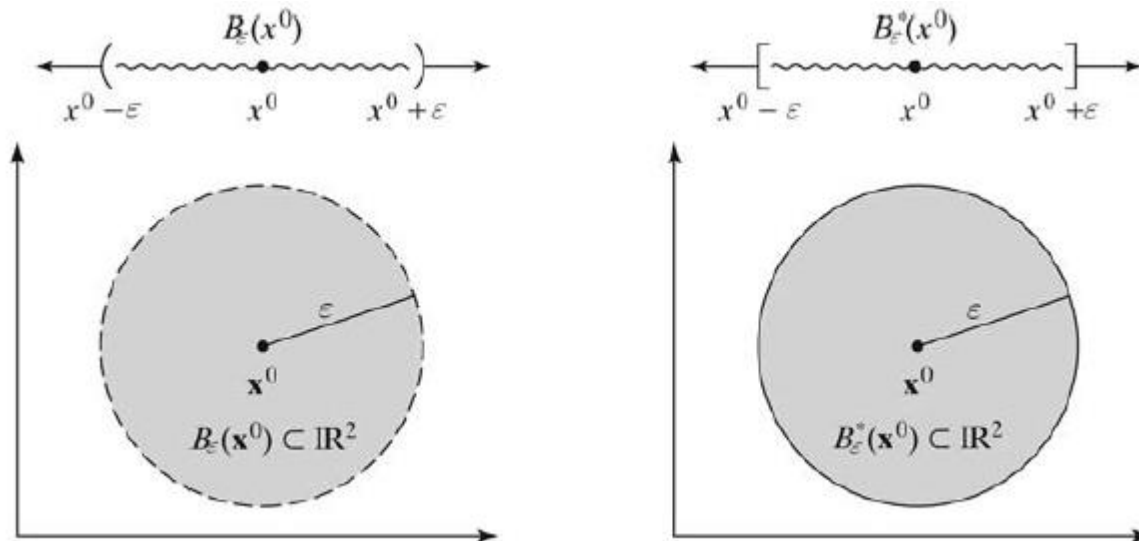
# Open and Closed $\varepsilon$ -Balls

1. The open  $\varepsilon$ -ball with centre  $\mathbf{x}^0$  and radius  $\varepsilon > 0$  (a real number) is the subset of points in  $\mathbb{R}^n$ :

$$B_\varepsilon(\mathbf{x}^0) \equiv \{ \mathbf{x} \in \mathbb{R}^n \mid \underbrace{d(\mathbf{x}^0, \mathbf{x})}_{\text{strictly less than}} < \varepsilon \}$$

2. The closed  $\varepsilon$ -ball with centre  $\mathbf{x}^0$  and radius  $\varepsilon > 0$  is the subset of points in  $\mathbb{R}^n$ :

$$B_\varepsilon^*(\mathbf{x}^0) \equiv \{ \mathbf{x} \in \mathbb{R}^n \mid \underbrace{d(\mathbf{x}^0, \mathbf{x})}_{\text{less than or equal to}} \leq \varepsilon \}$$



## **Open Sets in $\mathbb{R}^n$**

$S \subset \mathbb{R}^n$  is an open set if, for all  $\mathbf{x} \in S$ , there exists some  $\varepsilon > 0$  such that  $B_\varepsilon(\mathbf{x}) \subset S$ .

### **On Open Sets in $\mathbb{R}^n$**

1. The empty set,  $\emptyset$ , is an open set.
2. The entire space,  $\mathbb{R}^n$ , is an open set.
3. The union of open sets is an open set.
4. The intersection of any finite number of open sets is an open set.

## **Closed Sets in $\mathbb{R}^n$**

$S$  is a closed set if its complement,  $S^c$ , is an open set.

### **On Closed Sets in $\mathbb{R}^n$**

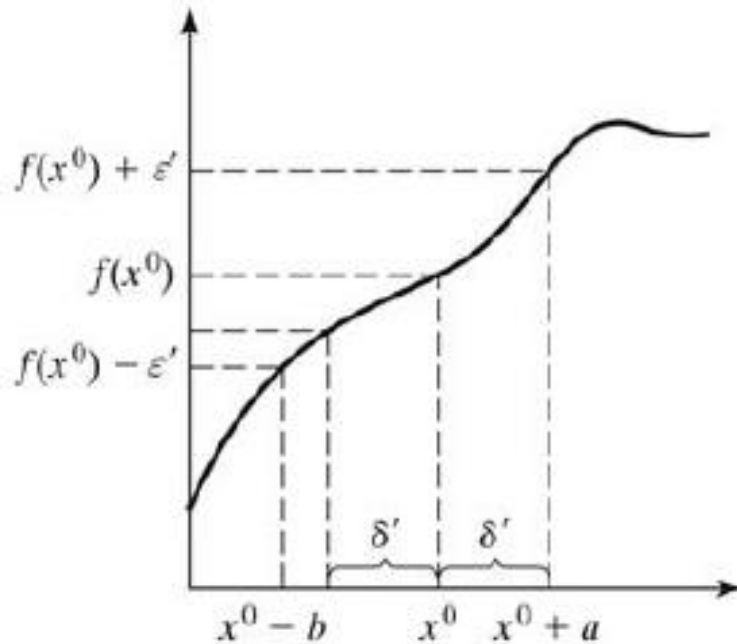
1. The empty set,  $\emptyset$ , is a closed set.
2. The entire space,  $\mathbb{R}^n$ , is a closed set.
3. The union of any finite collection of closed sets is a closed set.
4. The intersection of closed sets is a closed set.

## **Bounded Sets**

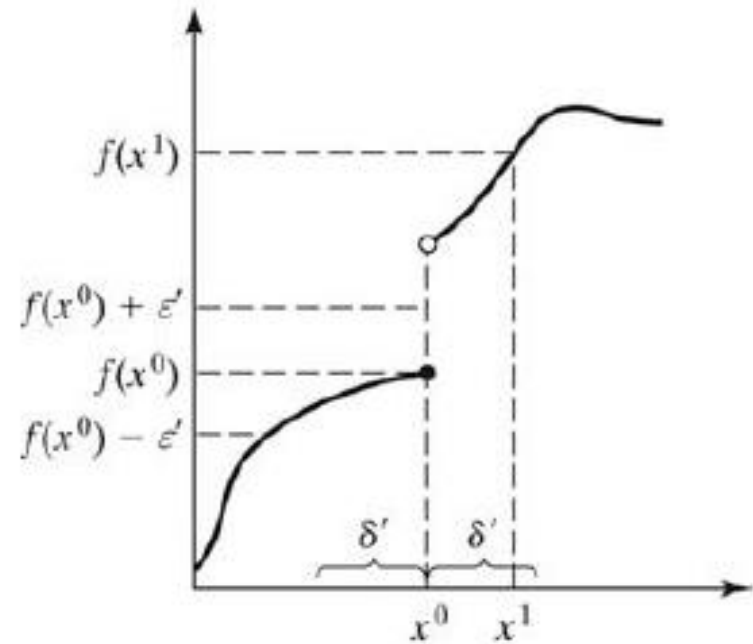
A set  $S$  in  $\mathbb{R}^n$  is called bounded if it is entirely contained within some  $\varepsilon$ -ball (either open or closed). That is,  $S$  is bounded if there exists some  $\varepsilon > 0$  such that  $S \subset B_\varepsilon(\mathbf{x})$  for some  $\mathbf{x} \in \mathbb{R}^n$ .

# Continuity

A function  $f: \mathbb{R} \rightarrow \mathbb{R}$  is *continuous at a point*  $x^0$  if, for all  $\varepsilon > 0$ , there exists a  $\delta > 0$  such that  $d(x, x^0) < \delta$  implies that  $d(f(x), f(x^0)) < \varepsilon$ . A function is called a *continuous function* if it is continuous at every point in its domain.



(a)



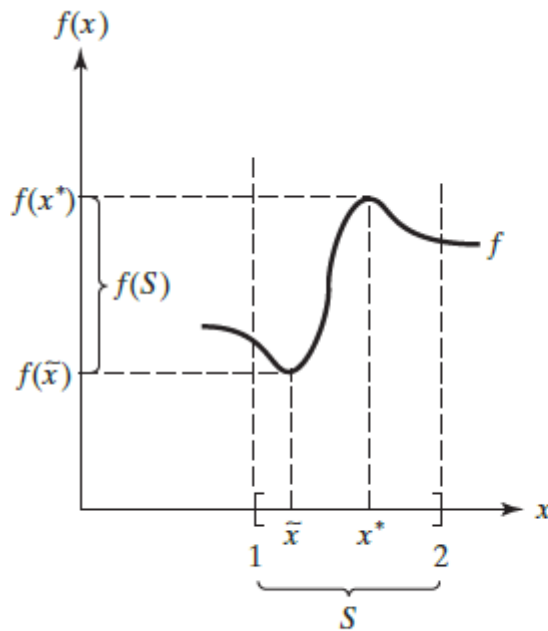
(b)

# Weierstrass Theorem

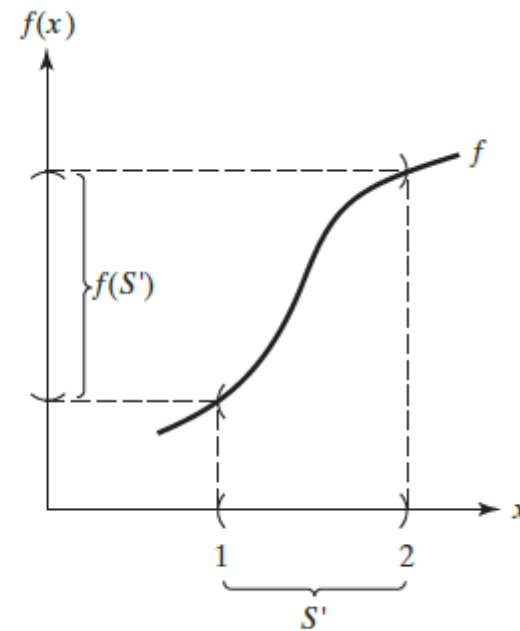
## *(Weierstrass) Existence of Extreme Values*

*Let  $f: S \rightarrow \mathbb{R}$  be a continuous real-valued mapping where  $S$  is a non-empty compact subset of  $\mathbb{R}^n$ . Then there exists a vector  $\mathbf{x}^* \in S$  and a vector  $\tilde{\mathbf{x}} \in S$  such that*

$$f(\tilde{\mathbf{x}}) \leq f(\mathbf{x}) \leq f(\mathbf{x}^*) \text{ for all } \mathbf{x} \in S.$$



(a)



(b)

# Real-Valued Functions

*$f: D \rightarrow \mathbb{R}$  is a real-valued function if  $D$  is any set and  $\mathbb{R} \subset \mathbb{R}$ .*

## **Increasing, Strictly Increasing and Strongly Increasing Functions**

*Let  $f: D \rightarrow \mathbb{R}$ , where  $D$  is a subset of  $\mathbb{R}^n$ . Then  $f$  is increasing if  $f(\mathbf{x}^0) \geq f(\mathbf{x}^1)$  whenever  $\mathbf{x}^0 \geq \mathbf{x}^1$ . If, in addition, the inequality is strict whenever  $\mathbf{x}^0 \gg \mathbf{x}^1$ , then we say that  $f$  is strictly increasing. If, instead,  $f(\mathbf{x}^0) > f(\mathbf{x}^1)$  whenever  $\mathbf{x}^0$  and  $\mathbf{x}^1$  are distinct and  $\mathbf{x}^0 \geq \mathbf{x}^1$ , then we say that  $f$  is strongly increasing.*

## **Decreasing, Strictly Decreasing and Strongly Decreasing Functions**

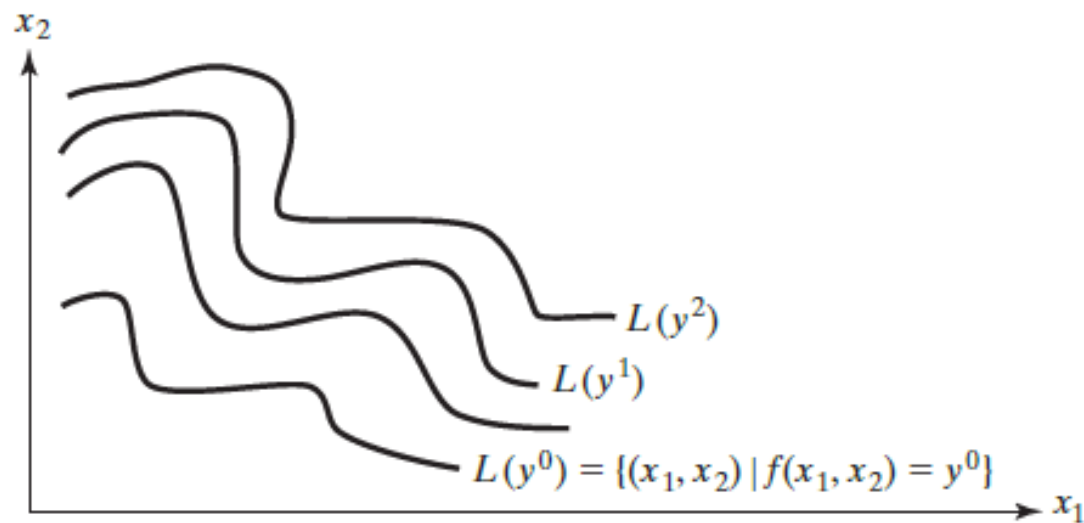
*Let  $f: D \rightarrow \mathbb{R}$ , where  $D$  is a subset of  $\mathbb{R}^n$ . Then  $f$  is decreasing if  $f(\mathbf{x}^0) \leq f(\mathbf{x}^1)$  whenever  $\mathbf{x}^0 \geq \mathbf{x}^1$ . If, in addition, the inequality is strict whenever  $\mathbf{x}^0 \gg \mathbf{x}^1$ , then we say that  $f$  is strictly decreasing. If, instead,  $f(\mathbf{x}^0) < f(\mathbf{x}^1)$  whenever  $\mathbf{x}^0$  and  $\mathbf{x}^1$  are distinct and  $\mathbf{x}^0 \geq \mathbf{x}^1$ , then we say that  $f$  is strongly decreasing.*



# Level Sets

## Level Sets

$L(y^0)$  is a level set of the real-valued function  $f: D \rightarrow \mathbb{R}$  iff  $L(y^0) = \{x \mid x \in D, f(x) = y^0\}$ , where  $y^0 \in \mathbb{R}$ .



## Superior and Inferior Sets

1.  $S(y^0) \equiv \{x \mid x \in D, f(x) \geq y^0\}$  is called the superior set for level  $y^0$ .
2.  $I(y^0) \equiv \{x \mid x \in D, f(x) \leq y^0\}$  is called the inferior set for level  $y^0$ .
3.  $S'(y^0) \equiv \{x \mid x \in D, f(x) > y^0\}$  is called the strictly superior set for level  $y^0$ .
4.  $I'(y^0) \equiv \{x \mid x \in D, f(x) < y^0\}$  is called the strictly inferior set for level  $y^0$ .

# Concave Functions

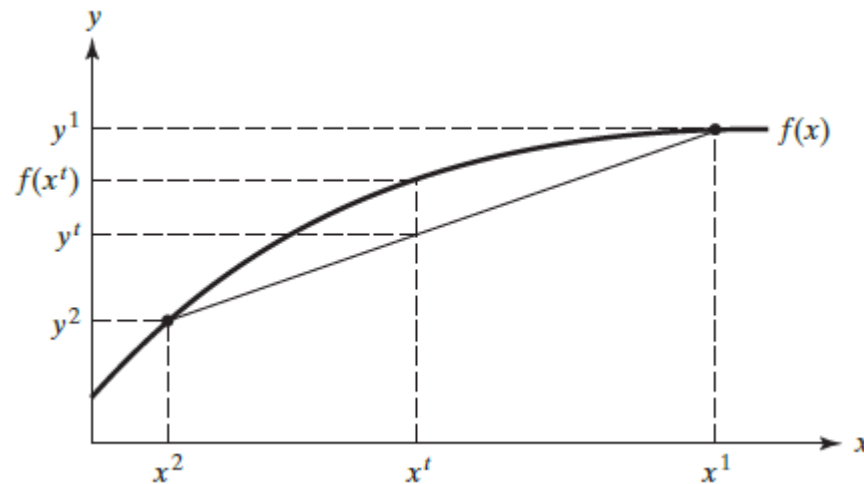
## Real-Valued Functions Over Convex Sets

Throughout this section, whenever  $f: D \rightarrow R$  is a real-valued function, we will assume  $D \subset \mathbb{R}^n$  is a convex set. When we take  $\mathbf{x}^1 \in D$  and  $\mathbf{x}^2 \in D$ , we will let  $\mathbf{x}^t \equiv t\mathbf{x}^1 + (1-t)\mathbf{x}^2$ , for  $t \in [0, 1]$ , denote the convex combination of  $\mathbf{x}^1$  and  $\mathbf{x}^2$ . Because  $D$  is a convex set, we know that  $\mathbf{x}^t \in D$ .

## Concave Functions

$f: D \rightarrow R$  is a concave function if for all  $\mathbf{x}^1, \mathbf{x}^2 \in D$ ,

$$f(\mathbf{x}^t) \geq tf(\mathbf{x}^1) + (1-t)f(\mathbf{x}^2) \quad \forall t \in [0, 1].$$



### **Points On and Below the Graph of a Concave Function Form a Convex Set**

*Let  $A \equiv \{(\mathbf{x}, y) \mid \mathbf{x} \in D, f(\mathbf{x}) \geq y\}$  be the set of points 'on and below' the graph of  $f: D \rightarrow R$ , where  $D \subset \mathbb{R}^n$  is a convex set and  $R \subset \mathbb{R}$ . Then,*

*$f$  is a concave function  $\iff A$  is a convex set.*

### **Strictly Concave Functions**

*$f: D \rightarrow R$  is a strictly concave function iff, for all  $\mathbf{x}^1 \neq \mathbf{x}^2$  in  $D$ ,*

$$f(\mathbf{x}^t) > tf(\mathbf{x}^1) + (1 - t)f(\mathbf{x}^2) \text{ for all } t \in (0, 1).$$

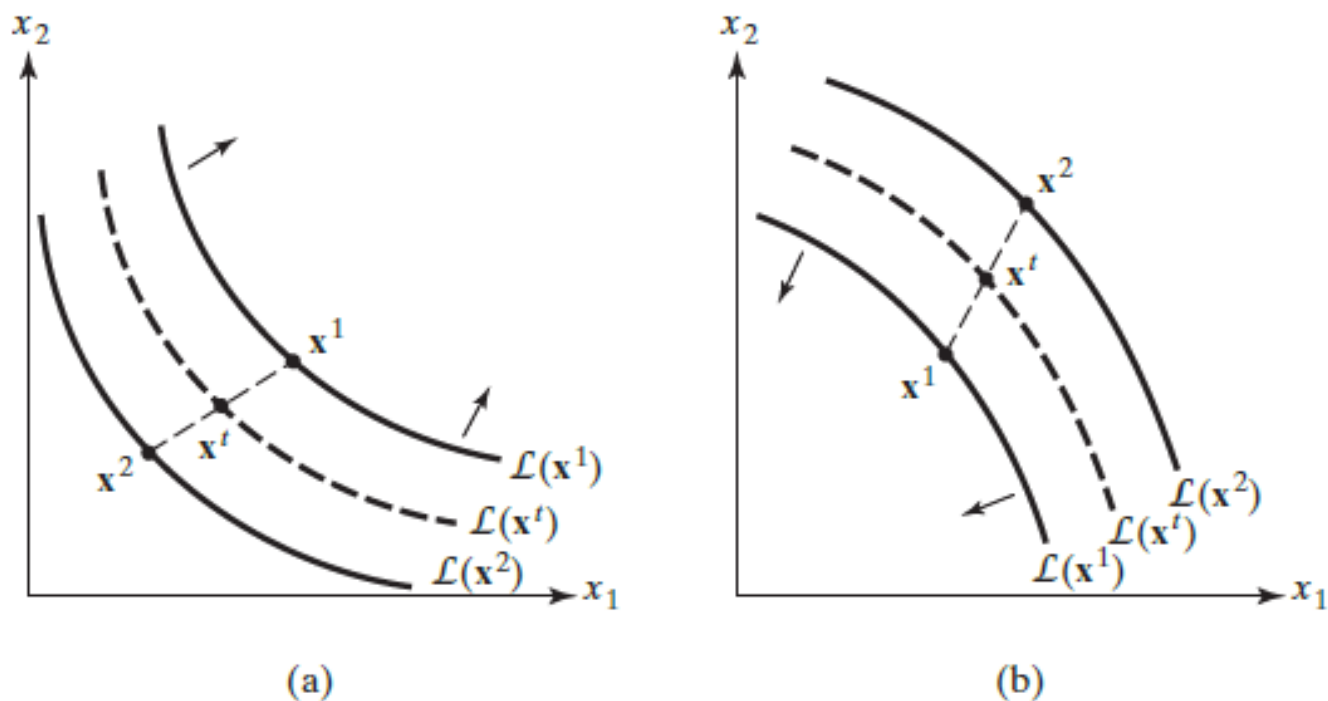
## Quasiconcave Functions<sup>7</sup>

$f: D \rightarrow \mathbb{R}$  is quasiconcave iff, for all  $\mathbf{x}^1$  and  $\mathbf{x}^2$  in  $D$ ,

$$f(\mathbf{x}^t) \geq \min[f(\mathbf{x}^1), f(\mathbf{x}^2)] \text{ for all } t \in [0, 1].$$

### Quasiconcavity and the Superior Sets

$f: D \rightarrow \mathbb{R}$  is a quasiconcave function iff  $S(y)$  is a convex set for all  $y \in \mathbb{R}$ .



**Figure A1.30.** Level sets for quasiconcave functions. (a) The function is quasiconcave and increasing. (b) The function is quasiconcave and decreasing.

## Concavity Implies Quasiconcavity

*A concave function is always quasiconcave. A strictly concave function is always strictly quasiconcave.*

## Convex and Strictly Convex Functions

1.  $f: D \rightarrow \mathbb{R}$  is a convex function iff, for all  $\mathbf{x}^1, \mathbf{x}^2$  in  $D$ ,

$$f(\mathbf{x}^t) \leq tf(\mathbf{x}^1) + (1 - t)f(\mathbf{x}^2) \text{ for all } t \in [0, 1].$$

2.  $f: D \rightarrow \mathbb{R}$  is a strictly convex function iff, for all  $\mathbf{x}^1 \neq \mathbf{x}^2$  in  $D$ ,

$$f(\mathbf{x}^t) < tf(\mathbf{x}^1) + (1 - t)f(\mathbf{x}^2) \text{ for all } t \in (0, 1).$$

## Concave and Convex Functions

*$f(\mathbf{x})$  is a (strictly) concave function if and only if  $-f(\mathbf{x})$  is a (strictly) convex function.*

## Points On and Above the Graph of a Convex Function Form a Convex Set

*Let  $A^* \equiv \{(\mathbf{x}, y) \mid \mathbf{x} \in D, f(\mathbf{x}) \leq y\}$  be the set of points 'on and above' the graph of  $f: D \rightarrow \mathbb{R}$ , where  $D \subset \mathbb{R}^n$  is a convex set and  $\mathbb{R} \subset \mathbb{R}$ . Then*

$$f \text{ is a convex function} \iff A^* \text{ is a convex set.}$$

## Quasiconvex and Strictly Quasiconvex Functions<sup>8</sup>

1. A function  $f: D \rightarrow \mathbb{R}$  is quasiconvex iff, for all  $\mathbf{x}^1, \mathbf{x}^2$  in  $D$ ,

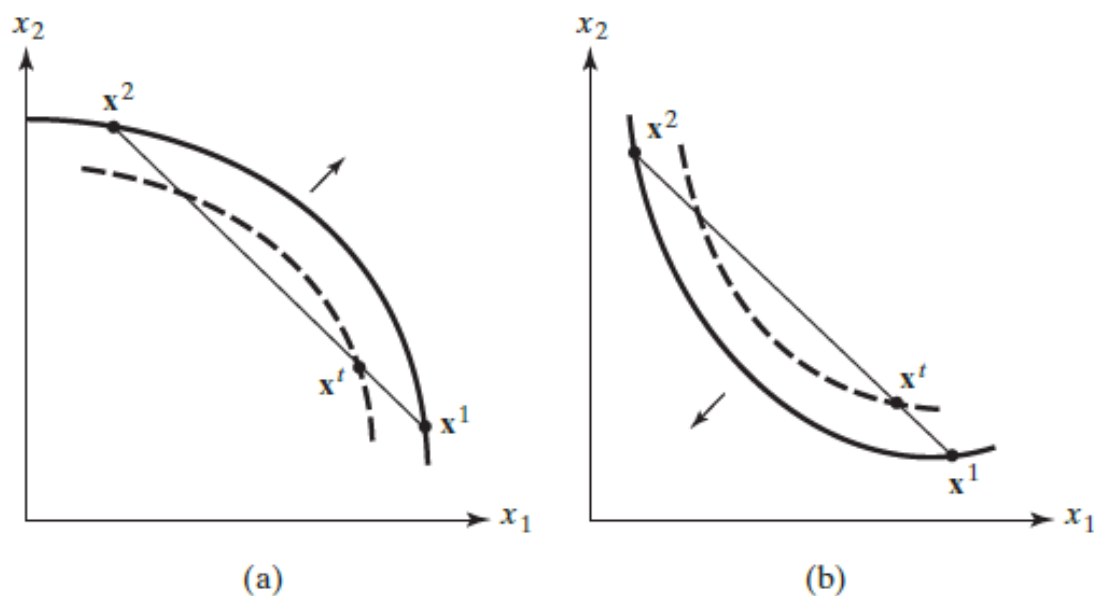
$$f(\mathbf{x}^t) \leq \max[f(\mathbf{x}^1), f(\mathbf{x}^2)] \quad \forall t \in [0, 1].$$

2. A function  $f: D \rightarrow \mathbb{R}$  is strictly quasiconvex iff, for all  $\mathbf{x}^1 \neq \mathbf{x}^2$  in  $D$ ,

$$f(\mathbf{x}^t) < \max[f(\mathbf{x}^1), f(\mathbf{x}^2)] \quad \forall t \in (0, 1).$$

## Quasiconvexity and the Inferior Sets

$f: D \rightarrow \mathbb{R}$  is a quasiconvex function iff  $I(y)$  is a convex set for all  $y \in \mathbb{R}$ .



**Figure A1.34.** Quasiconvex functions have convex inferior sets. Strictly quasiconvex functions have no linear segments in their level sets. (a) Strictly quasiconvex and increasing. (b) Strictly quasiconvex and decreasing.

# Summary

$f$ is concave	$\iff$ the set of points <i>beneath</i> the graph is convex
$f$ is convex	$\iff$ the set of points <i>above</i> the graph is convex
$f$ quasiconcave	$\iff$ superior sets are convex sets
$f$ quasiconvex	$\iff$ inferior sets are convex sets
$f$ concave	$\implies f$ quasiconcave
$f$ convex	$\implies f$ quasiconvex
$f$ (strictly) concave	$\iff -f$ (strictly) convex
$f$ (strictly) quasiconcave	$\iff -f$ (strictly) quasiconvex

# Calculus



# Functions of a single variable

## **Concavity and First and Second Derivatives**

*Let  $D$  be a non-degenerate interval of real numbers on the interior of which  $f$  is twice continuously differentiable. The following statements 1 to 3 are equivalent:*

- 1.  $f$  is concave.*
- 2.  $f''(x) \leq 0 \quad \forall$  non-endpoints  $x \in D$ .*
- 3. For all  $x^0 \in D$ :  $f(x) \leq f(x^0) + f'(x^0)(x - x^0) \quad \forall x \in D$ .*

*Moreover,*

- 4. If  $f''(x) < 0 \quad \forall$  non-endpoints  $x \in D$ , then  $f$  is strictly concave.*

# Functions of several variables

$$H(\mathbf{x}) = \begin{pmatrix} f_{11}(\mathbf{x}) & f_{12}(\mathbf{x}) & \dots & f_{1n}(\mathbf{x}) \\ f_{21}(\mathbf{x}) & f_{22}(\mathbf{x}) & \dots & f_{2n}(\mathbf{x}) \\ \vdots & \vdots & \ddots & \vdots \\ f_{n1}(\mathbf{x}) & f_{n2}(\mathbf{x}) & \dots & f_{nn}(\mathbf{x}) \end{pmatrix}$$

**The Hessian** of a function of several variables

## *Young's Theorem*

*For any twice continuously differentiable function  $f(\mathbf{x})$ ,*

$$\frac{\partial^2 f(\mathbf{x})}{\partial x_i \partial x_j} = \frac{\partial^2 f(\mathbf{x})}{\partial x_j \partial x_i} \quad \forall i \text{ and } j.$$

**→ The Hessian is symmetric**

# Homogeneous Functions

## **Homogeneous Functions**

*A real-valued function  $f(\mathbf{x})$  is called homogeneous of degree  $k$  if*

$$f(t\mathbf{x}) \equiv t^k f(\mathbf{x}) \quad \text{for all } t > 0.$$

*Two special cases are worthy of note:  $f(\mathbf{x})$  is homogeneous of degree 1, or linear homogeneous, if  $f(t\mathbf{x}) \equiv tf(\mathbf{x})$  for all  $t > 0$ ; it is homogeneous of degree zero if  $f(t\mathbf{x}) \equiv f(\mathbf{x})$  for all  $t > 0$ .*

## **Euler's Theorem**

*$f(\mathbf{x})$  is homogeneous of degree  $k$  if and only if*

$$kf(\mathbf{x}) = \sum_{i=1}^n \frac{\partial f(\mathbf{x})}{\partial x_i} x_i \quad \text{for all } \mathbf{x}.$$

# Unconstrained Optimization

## ***Necessary Conditions for Local Interior Optima in the Single-Variable Case***

*Let  $f(x)$  be a twice continuously differentiable function of one variable. Then  $f(x)$  reaches a local interior*

1. *maximum at  $x^* \Rightarrow f'(x^*) = 0$  (FONC),  
 $\Rightarrow f''(x^*) \leq 0$  (SONC).*
2. *minimum at  $\tilde{x} \Rightarrow f'(\tilde{x}) = 0$  (FONC),  
 $\Rightarrow f''(\tilde{x}) \geq 0$  (SONC).*

## ***First-Order Necessary Condition for Local Interior Optima of Real-Valued Functions***

*If the differentiable function  $f(\mathbf{x})$  reaches a local interior maximum or minimum at  $\mathbf{x}^*$ , then  $\mathbf{x}^*$  solves the system of simultaneous equations,*

$$\begin{aligned}\frac{\partial f(\mathbf{x}^*)}{\partial x_1} &= 0 \\ \frac{\partial f(\mathbf{x}^*)}{\partial x_2} &= 0 \\ &\vdots \\ \frac{\partial f(\mathbf{x}^*)}{\partial x_n} &= 0.\end{aligned}$$

# Unconstrained Optimization

## ***Second-Order Necessary Condition for Local Interior Optima of Real-Valued Functions***

*Let  $f(\mathbf{x})$  be twice continuously differentiable.*

- 1. If  $f(\mathbf{x})$  reaches a local interior maximum at  $\mathbf{x}^*$ , then  $\mathbf{H}(\mathbf{x}^*)$  is negative semidefinite.*
- 2. If  $f(\mathbf{x})$  reaches a local interior minimum at  $\tilde{\mathbf{x}}$ , then  $\mathbf{H}(\tilde{\mathbf{x}})$  is positive semidefinite.*

## ***Strict Concavity/Convexity and the Uniqueness of Global Optima***

- 1. If  $\mathbf{x}^*$  maximises the strictly concave function  $f$ , then  $\mathbf{x}^*$  is the unique global maximiser, i.e.,  $f(\mathbf{x}^*) > f(\mathbf{x}) \forall \mathbf{x} \in D, \mathbf{x} \neq \mathbf{x}^*$ .*
- 2. If  $\tilde{\mathbf{x}}$  minimises the strictly convex function  $f$ , then  $\tilde{\mathbf{x}}$  is the unique global minimiser, i.e.,  $f(\tilde{\mathbf{x}}) < f(\mathbf{x}) \forall \mathbf{x} \in D, \mathbf{x} \neq \tilde{\mathbf{x}}$ .*

# Constrained Optimization w/ Equality Constrains

$$\max_{x_1, x_2} f(x_1, x_2) \quad \text{subject to} \quad g(x_1, x_2) = 0.$$

$$\mathcal{L}(x_1, x_2, \lambda) \equiv f(x_1, x_2) - \lambda g(x_1, x_2).$$

$$\frac{\partial \mathcal{L}}{\partial x_1} = \frac{\partial f(x_1^*, x_2^*)}{\partial x_1} - \lambda^* \frac{\partial g(x_1^*, x_2^*)}{\partial x_1} = 0$$

$$\frac{\partial \mathcal{L}}{\partial x_2} = \frac{\partial f(x_1^*, x_2^*)}{\partial x_2} - \lambda^* \frac{\partial g(x_1^*, x_2^*)}{\partial x_2} = 0$$

$$\frac{\partial \mathcal{L}}{\partial \lambda} = g(x_1^*, x_2^*) = 0.$$

# Envelope Theorem

Describes how the optimal value of the objective function in a parametrized optimization problem changes as one of the parameters changes

Let  $f, h_1, \dots, h_k: R^n \times R^1 \rightarrow R^1$  be  $C^1$  functions. Let  $\mathbf{x}^*(a) = (x_1^*(a), x_2^*(a), \dots, x_n^*(a))$

denote the solution of the problem of:

$$\max f(\mathbf{x}, a)$$

*s.t.*

$$h_i(\mathbf{x}, a) = 0; \quad i = 1, \dots, k$$

for any fixed choice of the parameter  $a$ .

Suppose that  $\mathbf{x}^*(a)$  and the Lagrange multipliers  $\mu_1(a), \dots, \mu_k(a)$  are  $C^1$  functions and that the NDCQ holds. Then:

$$\frac{d}{da} f(\mathbf{x}^*(a), a) = \frac{\partial L}{\partial a}(\mathbf{x}^*(a), \mu(a), a),$$

where  $L$  is the natural Lagrangian for this problem.

# Comparative Statics

Consider a system of equations with 2 unknowns ( $x$  and  $y$ ) and a parameter  $t$ .

$$f(x, y, t) = 0$$

$$g(x, y, t) = 0$$

Determine

$$\frac{dx}{dt}$$



# Inverse Function Theorem

Let  $f$  be a  $C^1$  defined on an interval  $I$  in  $\mathbb{R}^1$ . If  $f'(x) \neq 0$  for all  $x \in I$ , then

a.)  $f$  is invertible on  $I$

b.) its inverse  $g$  is a  $C^1$  function on the interval  $f(I)$

c.) for all  $z$  in the domain of the inverse function  $g$

$$g'(z) = \frac{1}{f'(g(z))}$$