

# Chapter 1

## Topology and calculus background

We consider  $\mathbb{R}^n$  endowed with the scalar (or inner) product

$$x^T y = \sum_{i=1}^n x_i y_i$$

which induces the Euclidean norm

$$\|x\|_2 = \sqrt{x^T x} = \sqrt{\sum_{i=1}^n x_i^2}.$$

The following properties hold for any  $x, y \in \mathbb{R}^n$  and any  $\alpha \in \mathbb{R}$ :

$$\|x\|_2 \geq 0$$

$$\|\alpha x\|_2 = |\alpha| \|x\|_2$$

$$\|x\|_2 = 0 \iff x = 0$$

$$\|x + y\|_2 \leq \|x\|_2 + \|y\|_2$$

$$(\|x - y\|_2 \leq \|x\|_2 + \|y\|_2)$$

$$|x^T y| \leq \|x\|_2 \|y\|_2. \text{ (Schwarz inequality).}$$

In turn, the Euclidean norm induces the well-known Euclidean distance between the points  $x \in \mathbb{R}^n$  and  $y \in \mathbb{R}^n$ :

$$d(x, y) = \|x - y\|_2$$

and the following properties can be deduced from the above ones:

$$d(x, y) \geq 0$$

$$d(x, y) = 0 \iff x = y$$

$$d(x, y) \leq d(x, z) + d(z, x).$$

## 1.1 Sequences

A family of points  $\{x^k\}_{k \in \mathbb{N}} \subseteq \mathbb{R}^n$  (i.e.,  $\{x^1, x^2, \dots, x^k, \dots\}$ ) is called a *sequence*. For instance, the family of points  $x^k = (1/k, 1/k^2)$  is a sequence in  $\mathbb{R}^2$ .

**Definition 1.1.**  $\bar{x} \in \mathbb{R}^n$  is the *limit of a sequence*  $\{x^k\}_{k \in \mathbb{N}}$  if for each  $\varepsilon > 0$  there exists  $\bar{k} \in \mathbb{N}$  such that  $d(x^k, \bar{x}) \leq \varepsilon$  for all  $k \geq \bar{k}$ , or equivalently

$$\forall \varepsilon > 0 \quad \exists \bar{k} \in \mathbb{N} \quad \text{s.t.} \quad \|x^k - \bar{x}\|_2 \leq \varepsilon \quad \forall k \geq \bar{k}.$$

If it exists, the limit of a sequence is unique. Standard notations to denote a limit are the following:  $\lim_{k \rightarrow +\infty} x^k = \bar{x}$ ,  $x^k \rightarrow \bar{x}$  ( $k \rightarrow +\infty$  below the arrow is often omitted).

**Example 1.1.** The limit of the sequence  $(1/k, 1/k^2)$  is  $\bar{x} = (0, 0)$ , while the sequence  $x^k = (1/k, (-1)^k)$  does not have a limit. Take the sequence obtained just considering odd indices:  $x^1, x^3, x^5, \dots$ . This sequence converges to  $(0, -1)$ . Analogously, the sequence obtained considering just even indices converges to  $(0, 1)$ .

**Definition 1.2.**  $\{x^{k_j}\}_{j \in \mathbb{N}} \subseteq \{x^k\}_{k \in \mathbb{N}}$  is a *subsequence* if  $k_j \rightarrow +\infty$  as  $j \rightarrow +\infty$ .

**Definition 1.3.**  $\bar{x} \in \mathbb{R}^n$  is a *cluster point* of  $\{x^k\}_{k \in \mathbb{N}}$  if there exists a subsequence  $\{x^{k_j}\}_{j \in \mathbb{N}}$  such that  $\bar{x}$  is its limit, i.e.,  $\lim_{j \rightarrow +\infty} x^{k_j} = \bar{x}$ , or equivalently

$$\forall \varepsilon > 0 \quad \forall k \in \mathbb{N} \quad \exists \bar{k} \geq k \quad \text{s.t.} \quad \|x^{\bar{k}} - \bar{x}\|_2 \leq \varepsilon.$$

If a sequence has a limit, then it is the unique cluster point of the sequence.

**Example 1.2.** The last sequence of Example 1.1 has 2 cluster points:  $(0, 1)$  and  $(0, -1)$ , while the sequence  $y^k = (k, 1/k)$  does not have any cluster point.

**Theorem 1.1. (Bolzano-Weierstrass)** *If the norm of all the points of a sequence  $\{x^k\}_{k \in \mathbb{N}}$  do not exceed a threshold value, i.e., there exists  $M > 0$  such that  $\|x^k\|_2 \leq M$  holds for all  $k \in \mathbb{N}$ , then the sequence has at least one cluster point.*

## 1.2 Topological properties in the Euclidean space

The open ball of centre  $x \in \mathbb{R}^n$  and radius  $\varepsilon > 0$  is the set

$$B(x, \varepsilon) = \{y \in \mathbb{R}^n : \|y - x\|_2 < \varepsilon\}.$$

**Definition 1.4.**

(i)  $D \subseteq \mathbb{R}^n$  is called *open* if

$$\forall x \in D \quad \exists \varepsilon > 0 \quad \text{s.t.} \quad B(x, \varepsilon) \subseteq D.$$

(ii)  $x \in D$  is called an *interior point* of  $D$  if

$$\exists \varepsilon > 0 \quad \text{s.t.} \quad B(x, \varepsilon) \subseteq D.$$

The set of the interior points of  $D$  is called *the interior of  $D$*  and it is generally denoted by  $\text{int } D$ . Notice that a set  $D$  is open if and only if  $D = \text{int } D$ .

**Example 1.3.**  $B(x, \varepsilon)$ ,  $\mathbb{R}^n$ ,  $\emptyset$  are open sets in  $\mathbb{R}^n$  while the interval  $] - 1, 1[$  is an open set in  $\mathbb{R}$ .

**Proposition 1.1.**

- (i) *The union of a family of open sets is an open set.*
- (ii) *The intersection of a finite family of open sets is an open set.*

The finiteness of the family is crucial for the intersection property:

$$\bigcap_{k=1}^{+\infty} B(0, 1/k) = \{0\}.$$

**Definition 1.5.**

- (i)  $D \subseteq \mathbb{R}^n$  is called *closed* if  $\mathbb{R}^n \setminus D = \{x \in \mathbb{R}^n : x \notin D\}$  is open.
- (ii)  $x \in \mathbb{R}^n$  is called an *closure point* of  $D$  if

$$\forall \varepsilon > 0 : B(x, \varepsilon) \cap D \neq \emptyset.$$

The set of the closure points of  $D$  is called *the closure of  $D$*  and it is generally denoted by  $\text{cl } D$  or  $\overline{D}$ .

**Proposition 1.2.**

- (i)  *$D$  is closed if and only if  $D = \text{cl } D$ .*
- (ii)  *$D$  is closed if and only if the limit of any convergent sequence contained in  $D$  belongs to  $D$  as well, i.e.,*

$$\forall \{x^k\}_{k \in \mathbb{N}} \subseteq D \quad \text{s.t.} \quad \exists \bar{x} \in \mathbb{R}^n \quad \text{s.t.} \quad x^k \longrightarrow \bar{x} : \bar{x} \in D.$$

**Example 1.4.**  $\mathbb{R}^n$ ,  $\emptyset$ ,  $\{y \in \mathbb{R}^n : \|y - x\|_2 \leq \varepsilon\} = \overline{B(x, \varepsilon)}$  are closed sets in  $\mathbb{R}^n$  while the interval  $[-1, 1]$  is a closed set in  $\mathbb{R}$ . There exist sets which are neither closed nor open, for instance the interval  $[-1, 1[$  in  $\mathbb{R}$  and

$$D = [-1, 0] \times [-1, 1] \cup B(0, 1) \subseteq \mathbb{R}^2.$$

In fact,  $(-1 - \varepsilon, 0) \notin D$  but  $(-1 - \varepsilon, 0) \in B((-1, 0), \varepsilon)$  for any  $\varepsilon > 0$  so that  $D$  is not open, and  $x^k = (1 - 1/k, 0) \in D$  for any  $k \in \mathbb{N}$  while  $x^k \rightarrow (1, 0) \notin D$  so that  $D$  is not closed.

**Proposition 1.3.**

- (i) *The union of a finite family of closed sets is an closed set.*

(ii) *The intersection of a family of closed sets is a closed set.*

The finiteness of the family is crucial for the union property:

$$\bigcup_{k=2}^{+\infty} \overline{B(0, 1 - 1/k)} = B(0, 1).$$

**Definition 1.6.**  $x \in \mathbb{R}^n$  is called a *boundary point* of  $D$  if both

$$B(x, \varepsilon) \cap D \neq \emptyset \quad \text{and} \quad B(x, \varepsilon) \not\subseteq D$$

hold for any  $\varepsilon > 0$ .

The set of the boundary points of  $D$  is called *the boundary (or frontier) of  $D$*  and it is generally denoted by  $\partial D$ . Notice that  $\partial D = \overline{D} \cap (\mathbb{R}^n \setminus D)$ .

**Proposition 1.4.**  $D \subseteq \mathbb{R}^n$  is both closed and open if and only if  $D = \mathbb{R}^n$  or  $D = \emptyset$ .

**Definition 1.7.**

(i)  $D \subseteq \mathbb{R}^n$  is called *bounded* if

$$\exists M > 0 \quad \text{s.t.} \quad \forall x \in D : \|x\|_2 \leq M.$$

(ii)  $D \subseteq \mathbb{R}^n$  is called *compact* if it is bounded and closed.

The set  $D$  in Example 1.4 is bounded but it is not compact (since it is not closed).

The Bolzano-Weierstrass' theorem can be enhanced in the following way.

**Theorem 1.2. (Bolzano-Weierstrass)** *A set is compact if and only if any sequence contained in the set has at least one cluster point and all its cluster points belong to the set.*

## 1.3 Functions of several variables

### 1.3.1 Continuity

**Definition 1.8.**  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  is called *continuous at  $\bar{x} \in \mathbb{R}^n$*  if  $f(\bar{x})$  is the limit of  $f(x)$  as  $x \rightarrow \bar{x}$ , i.e.,

$$\forall \varepsilon > 0 \quad \exists \delta > 0 \quad \text{s.t.} \quad \|x - \bar{x}\|_2 \leq \delta \implies |f(x) - f(\bar{x})| \leq \varepsilon.$$

$f$  is continuous on a set  $D \subseteq \mathbb{R}^n$  if it is continuous at every  $x \in D$ .

**Proposition 1.5.**  $f$  is continuous at  $\bar{x} \in \mathbb{R}^n$  if and only if any sequence  $\{x^k\}_{k \in \mathbb{N}}$  such that  $x^k \rightarrow \bar{x}$  satisfies  $f(x^k) \rightarrow f(\bar{x})$ .

**Example 1.5.**  $f(x) = \|x\|_2$  is a continuous function on  $\mathbb{R}^n$ ,  $f(x_1, x_2) = \sin(\pi x_1 x_2)$  is a continuous function on  $\mathbb{R}^2$ .

**Theorem 1.3. (Weierstrass)** Let  $D \subseteq \mathbb{R}^n$  be compact and  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  continuous on  $D$ . Then, there exist at least one minimum point  $\bar{x} \in D$  and one maximum point  $\hat{x} \in D$  for  $f$  over  $D$ , i.e.,

$$f(\bar{x}) = \min\{f(x) : x \in D\} \quad \text{and} \quad f(\hat{x}) = \max\{f(x) : x \in D\}.$$

**Proof.** Let  $\ell = \inf\{f(x) : x \in D\} \in [-\infty + \infty[$  and consider any minimizing sequence, that is any  $\{x^k\}_{k \in \mathbb{N}}$  such that  $f(x^k) \rightarrow \ell$ . Since  $D$  is compact, there exist a subsequence  $\{x^{k_j}\}_{j \in \mathbb{N}}$  and  $\bar{x} \in D$  such that  $x^{k_j} \rightarrow \bar{x}$  (as  $j \rightarrow +\infty$ ) by Theorem 1.2. Since  $f$  is continuous,  $f(x^{k_j}) \rightarrow f(\bar{x})$  and therefore  $f(\bar{x}) = \ell$  by the uniqueness of the limit. As a consequence,  $\ell \neq -\infty$  and  $f(\bar{x}) = \min\{f(x) : x \in D\}$ . The existence of  $\hat{x}$  can be proved analogously.  $\square$

**Example 1.6.** Take  $n = 1$ ,  $f(x) = e^{-x}$  and  $D = \mathbb{R}_+$ :  $f$  is continuous on  $D$ ,  $\inf\{f(x) : x \in D\} = 0$  but there exists no  $x \in D$  such that  $f(x) = 0$ . Indeed,  $D$  is not compact as it is not bounded.

### 1.3.2 Partial derivatives and differentiability

A point  $d \in \mathbb{R}^n$  such that  $\|d\|_2 = 1$  is also called a *direction*, and the set

$$\{\bar{x} + td : t \in \mathbb{R}\}$$

describes the line of direction  $d$  passing through  $\bar{x} \in \mathbb{R}^n$ . If only  $t \in \mathbb{R}_+$  are considered, the set describes the corresponding half-line.

Just like the case  $n = 1$ , the key tool for developing calculus for a function  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  is the *incremental ratio*

$$icr_{(f,x,d)}(t) = [f(x + td) - f(x)]/t.$$

**Definition 1.9.**  $f$  has a derivative at  $\bar{x}$  in the direction  $d$  if the derivative of the function of one variable  $icr_{(f,\bar{x},d)}$  at  $t = 0$  exists, that is  $\lim_{t \rightarrow 0} [f(\bar{x} + td) - f(\bar{x})]/t$  exists. In that case

$$\frac{\partial f}{\partial d}(\bar{x}) = \lim_{t \rightarrow 0} \frac{f(\bar{x} + td) - f(\bar{x})}{t}$$

is called the (*directional*) *derivative of  $f$  at  $\bar{x}$  in the direction  $d$* . For  $n = 1$  there exists a unique (up to the sign) direction and the directional derivative coincides with the (usual) derivative and it is also denoted by  $f'(\bar{x})$ .

If  $d$  is one of the vectors of the canonical basis  $\{e_1, \dots, e_n\}$  of  $\mathbb{R}^n$ , namely  $d = e_i$ , then the corresponding directional derivative is called *partial derivative* and denoted by  $\partial f(x)/\partial x_i$  rather than  $\partial f(x)/\partial e_i$ . Indeed, the derivative can be computed considering  $f$  as a function of  $x_i$  while the other variables are kept fixed like parameters:

$$\frac{\partial f}{\partial x_i}(\bar{x}) = \lim_{t \rightarrow 0} \frac{f(\bar{x}_1, \dots, \bar{x}_{i-1}, \bar{x}_i + t, \bar{x}_{i+1}, \dots, \bar{x}_n) - f(\bar{x})}{t}$$

**Definition 1.10.** If  $f$  has all the partial derivatives at  $\bar{x} \in \mathbb{R}^n$ , the vector

$$\nabla f(\bar{x}) = \left( \frac{\partial f}{\partial x_1}(\bar{x}), \frac{\partial f}{\partial x_2}(\bar{x}), \dots, \frac{\partial f}{\partial x_n}(\bar{x}) \right)^T$$

is called the *gradient of  $f$  at  $\bar{x}$* .

**Example 1.7.** Take  $n = 2$  and  $f(x_1, x_2) = \sin(\pi x_1 x_2)$ :

$$\frac{\partial f}{\partial x_1}(x) = \pi x_2 \cos(\pi x_1 x_2), \quad \frac{\partial f}{\partial x_2}(\bar{x}) = \pi x_1 \cos(\pi x_1 x_2).$$

Other directional derivatives can be defined just considering the limit of the incremental ratio as  $t \rightarrow 0^+$ , that is  $t \rightarrow 0$  for only positive  $t$  ( $t > 0$ ).

**Definition 1.11.** The limit

$$f'(\bar{x}; d) = \lim_{t \rightarrow 0^+} \frac{f(\bar{x} + td) - f(\bar{x})}{t}$$

is called the *one-sided directional derivative of  $f$  at  $\bar{x}$  in the direction  $d$* .

Clearly,  $f'(\bar{x}; d) = \partial f(\bar{x})/\partial d$  if the latter exists but this is not always the case.

**Example 1.8.** Consider  $f(x) = \|x\|_2$  and take  $\bar{x} = 0$ :

$$[f(\bar{x} + td) - f(\bar{x})]/t = \|td\|_2/t = |t|\|d\|_2/t = \operatorname{sgn}(t)\|d\|_2$$

where  $\operatorname{sgn}(t)$  denotes the sign of  $t$  ( $\operatorname{sgn}(t) = 1$  if  $t \geq 0$  and  $\operatorname{sgn}(t) = -1$  if  $t < 0$ ). Therefore,  $f'(\bar{x}; d) = \|d\|_2$  while  $\partial f(\bar{x})/\partial d$  does not exist.

Unlike the case  $n = 1$ , the existence of the directional/partial derivatives does not guarantee the continuity of the function.

**Example 1.9.** Take  $n = 2$  and

$$f(x_1, x_2) = \begin{cases} [x_1^2 x_2 / (x_1^4 + x_2^2)]^2 & \text{if } (x_1, x_2) \neq (0, 0) \\ 0 & \text{if } (x_1, x_2) = (0, 0). \end{cases}$$

Consider the parabola  $x_2 = \alpha x_1^2$  for  $x_1 \neq 0$ :

$$f(x_1, \alpha x_1^2) = [\alpha x_1^4 / (x_1^4 + \alpha^2 x_1^4)]^2 = \alpha^2 / (1 + \alpha^2)^2.$$

Therefore,  $f$  is not continuous at  $\bar{x} = (0, 0)$ : take the sequence  $x^k = (1/k, 1/k^2)$  to get  $x^k \rightarrow \bar{x}$  while  $f(x^k) \equiv 1/4$ . On the other hand,  $f$  has the directional derivative at  $\bar{x}$  in each direction  $d$ :

$$\frac{\partial f}{\partial d}(\bar{x}) = \lim_{t \rightarrow 0} [t^3 d_1^2 d_2 / t^2 (t^2 d_1^4 + d_2^2)]^2 / t = \lim_{t \rightarrow 0} t d_1^4 d_2^2 / ((t^2 d_1^4 + d_2^2)^2) = 0.$$

**Definition 1.12.**  $f$  is called *differentiable at*  $\bar{x} \in \mathbb{R}^n$  if there exists a linear function  $L : \mathbb{R}^n \rightarrow \mathbb{R}$  such that

$$\forall v \in \mathbb{R}^n : f(\bar{x} + v) = f(\bar{x}) + L(v) + r(v)$$

for some residual function  $r$  such that  $r(v)/\|v\|_2 \rightarrow 0$  as  $\|v\|_2 \rightarrow 0$ . If  $f$  is differentiable at  $\bar{x}$ ,  $L$  is called the *differential of  $f$  at  $\bar{x}$* . Notice that both  $L$  and  $r$  depend not only on  $f$  but also on the considered point  $\bar{x}$ .

$f$  is differentiable on a set  $D \subseteq \mathbb{R}^n$  if it is differentiable at every  $x \in D$ .

Recall that  $L : \mathbb{R}^n \rightarrow \mathbb{R}$  is linear if

$$\forall x, y \in \mathbb{R}^n \forall \alpha, \beta \in \mathbb{R} : L(\alpha x + \beta y) = \alpha L(x) + \beta L(y).$$

$L$  is linear if and only if there exists  $\ell \in \mathbb{R}^n$  such that  $L(x) = \ell^T x$  for all  $x \in \mathbb{R}^n$ .

**Proposition 1.6.** *Suppose  $f$  is differentiable at  $\bar{x} \in \mathbb{R}^n$ . Then,*

(i)  $f$  is continuous at  $\bar{x}$ ;

(ii)  $f$  has directional derivatives at  $\bar{x}$  in each direction  $d$  and  $\frac{\partial f}{\partial d}(\bar{x}) = L(d)$ ;

(iii)  $L(d) = \nabla f(\bar{x})^T d$ .

**Proof.** (i) It is enough to apply Definition 1.12 just taking  $h = x - \bar{x}$  as  $x \rightarrow \bar{x}$ .

(ii) Take any direction  $d \in \mathbb{R}^n$ . Then, Definition 1.12 implies

$$\begin{aligned} \frac{\partial f}{\partial d}(\bar{x}) &= \lim_{t \rightarrow 0} (f(\bar{x} + td) - f(\bar{x}))/t \\ &= \lim_{t \rightarrow 0} (L(td) + r(td))/t \\ &= \lim_{t \rightarrow 0} (tL(d) + r(td))/t \\ &= L(d) + \lim_{t \rightarrow 0} r(td)/t \\ &= L(d) + \lim_{t \rightarrow 0} \operatorname{sgn}(t) (r(td))/\|td\|_2 = L(d). \end{aligned}$$

(iii) Since  $d = \sum_{i=1}^n d_i e_i$ , (ii) implies

$$\frac{\partial f}{\partial d}(\bar{x}) = L(d) = L\left(\sum_{i=1}^n d_i e_i\right) = \sum_{i=1}^n d_i L(e_i) = \sum_{i=1}^n d_i \frac{\partial f}{\partial x_i}(\bar{x}) = \nabla f(\bar{x})^T d. \quad \square$$

Proposition 1.6 (iii) allows to restate the definition of differentiability through (the first order) Taylor's formula:

**Taylor's formula**  $f(\bar{x} + v) = f(\bar{x}) + \nabla f(\bar{x})^T v + r(v) \quad (r(v)/\|v\|_2 \rightarrow 0)$

Considering any  $v = x - \bar{x} \approx 0$ , Taylor's formula states that  $f(x)$  can be approximated by an affine function, namely  $f(x) \approx f(\bar{x}) + \nabla f(\bar{x})^T (x - \bar{x})$ , and the closer  $x$  is to  $\bar{x}$  the better the approximation is. Indeed, the set

$$\{(x, f(\bar{x}) + \nabla f(\bar{x})^T (x - \bar{x})) : x \in \mathbb{R}^n\}$$

is the tangent hyperplane to the graph  $\{(x, f(x)) : x \in \mathbb{R}^n\}$  of  $f$  at  $(\bar{x}, f(\bar{x}))$ .

**Theorem 1.4.** Let  $\bar{x} \in \mathbb{R}^n$  and suppose  $f$  has all the partial derivatives at each  $x \in B(\bar{x}, \varepsilon)$  for some  $\varepsilon > 0$ . Then, if the functions  $x \mapsto \partial f(x)/\partial x_i$  are continuous at  $\bar{x}$  for all  $i = 1, \dots, n$ , then  $f$  is differentiable at  $\bar{x}$ .

**Example 1.10.** Take  $n = 2$  and

$$f(x_1, x_2) = \begin{cases} x_1^2 x_2 / (x_1^2 + x_2^2) & \text{if } (x_1, x_2) \neq (0, 0) \\ 0 & \text{if } (x_1, x_2) = (0, 0) \end{cases}$$

and consider  $\bar{x} = (0, 0)$ :  $f$  is continuous but not differentiable at  $\bar{x}$ . In fact, the derivative of  $f$  at  $\bar{x}$  in the direction  $d$  is

$$\frac{\partial f}{\partial d}(\bar{x}) = \lim_{t \rightarrow 0} [t^3 d_1^2 d_2 / t^2 (d_1^2 + d_2^2)] / t = d_1^2 d_2$$

since  $1 = \|d\|_2^2 = d_1^2 + d_2^2$ . As a consequence,  $\partial f(\bar{x})/\partial x_1 = \partial f(\bar{x})/\partial x_2 = 0$  while  $\partial f(\bar{x})/\partial d \neq 0$  for all  $d \neq e_1, e_2$  so that  $\partial f(\bar{x})/\partial d \neq \nabla f(\bar{x})^T d$  (see Proposition 1.6).

Notice that

$$\frac{\partial f}{\partial x_1}(x) = 2x_1 x_2^3 / (x_1^2 + x_2^2)^2 \quad (x \neq \bar{x})$$

is not continuous at  $\bar{x}$  (in accordance with Theorem 1.4):  $x^k = (1/k, 1/k) \rightarrow \bar{x}$  while  $\partial f(x^k)/\partial x_1 \equiv 1/2$  and  $\partial f(\bar{x})/\partial x_1 = 0$ .

**Definition 1.13.**  $f$  is called *continuously differentiable* at  $\bar{x} \in \mathbb{R}^n$  if there exists  $\varepsilon > 0$  such that  $f$  is differentiable at each  $x \in B(\bar{x}, \varepsilon)$  and the partial derivatives are continuous at  $\bar{x}$ .  $f$  is continuously differentiable on a set  $D \subseteq \mathbb{R}^n$  if it is continuously differentiable at every  $x \in D$ .

**Theorem 1.5. (mean value)** Suppose  $f$  is continuously differentiable (on  $\mathbb{R}^n$ ). Given any  $\bar{x}, v \in \mathbb{R}^n$ , there exists  $t \in ]0, 1[$  such that

$$f(\bar{x} + v) = f(\bar{x}) + \nabla f(\bar{x} + tv)^T v.$$

**Theorem 1.6. (upper estimate)** Suppose  $f$  is continuously differentiable (on  $\mathbb{R}^n$ ) and the gradient mapping  $\nabla f$  is Lipschitz with modulus  $L > 0$ , i.e.,

$$\forall x, v \in \mathbb{R}^n : \|\nabla f(x) - \nabla f(v)\|_2 \leq L\|x - v\|_2.$$

Then, any  $x, v \in \mathbb{R}^n$  satisfy  $f(x + v) \leq f(x) + \nabla f(\bar{x} + v)^T v + L\|v\|_2^2/2$ .

**Proposition 1.7. (chain rules)**

- (i) If  $g : \mathbb{R}^n \rightarrow \mathbb{R}$  is differentiable at  $\bar{x} \in \mathbb{R}^n$  and  $h : \mathbb{R} \rightarrow \mathbb{R}$  has a derivative at  $f(\bar{x})$ , then  $f = h \circ g$  is differentiable at  $\bar{x}$  and  $\nabla f(\bar{x}) = h'(g(\bar{x}))\nabla g(\bar{x})$ .
- (ii) Let  $h = (h_1, \dots, h_n) : \mathbb{R} \rightarrow \mathbb{R}^n$  and  $g : \mathbb{R}^n \rightarrow \mathbb{R}$ . If the functions  $h_i : \mathbb{R} \rightarrow \mathbb{R}$  have a derivative at  $\bar{t} \in \mathbb{R}$  for all  $i = 1, \dots, n$  and  $g$  is differentiable at  $h(\bar{t}) \in \mathbb{R}^n$ , then  $g \circ h$  has a derivative at  $\bar{t}$  and  $(g \circ h)'(\bar{t}) = \nabla g(h(\bar{t}))^T h'(\bar{t})$  where  $h'(\bar{t}) = (h'_1(\bar{t}), \dots, h'_n(\bar{t}))^T$ .

**Definition 1.14.** Let  $F = (f_1, \dots, f_m) : \mathbb{R}^n \rightarrow \mathbb{R}^m$ . If the functions  $f_i : \mathbb{R}^n \rightarrow \mathbb{R}$  have all the partial derivatives at  $\bar{x} \in \mathbb{R}^n$  for all  $i = 1, \dots, m$ , then

$$JF(\bar{x}) = \begin{bmatrix} \nabla f_1(\bar{x})^T \\ \vdots \\ \nabla f_m(\bar{x})^T \end{bmatrix} = \begin{bmatrix} \frac{\partial f_1}{\partial x_1}(\bar{x}) & \cdots & \frac{\partial f_1}{\partial x_n}(\bar{x}) \\ \vdots & \vdots & \vdots \\ \frac{\partial f_m}{\partial x_1}(\bar{x}) & \cdots & \frac{\partial f_m}{\partial x_n}(\bar{x}) \end{bmatrix} \in \mathbb{R}^{m \times n}$$

is called the *Jacobian matrix* of  $F$  at  $\bar{x}$ .

### 1.3.3 Second-order derivatives

If a function  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  is differentiable on the whole  $\mathbb{R}^n$ , then each directional derivative exists at each point  $x \in \mathbb{R}^n$ . In this case, the derivative in the direction  $d$  is the function  $\partial f / \partial d : \mathbb{R}^n \rightarrow \mathbb{R}$  such that  $(\partial f / \partial d)(x) = \partial f(x) / \partial d$ . If it has a derivative in the direction  $v$ , then

$$\frac{\partial}{\partial v} \left( \frac{\partial f}{\partial d} \right) (x) = \lim_{t \rightarrow 0} \left[ \frac{\partial f}{\partial d}(x + tv) - \frac{\partial f}{\partial d}(x) \right] / t$$

is generally denoted by  $\partial^2 f(x) / \partial v \partial d$ .

**Definition 1.15.**  $f$  has *second-order partial derivatives* at  $\bar{x} \in \mathbb{R}^n$  if it has the (first-order) partial derivatives at each  $x \in B(\bar{x}, \varepsilon)$  for some  $\varepsilon > 0$  and they have partial derivatives at  $\bar{x}$  as well, namely

$$\frac{\partial^2 f}{\partial x_i \partial x_j} (x) = \lim_{t \rightarrow 0} \left[ \frac{\partial f}{\partial x_j}(\bar{x} + tv) - \frac{\partial f}{\partial x_j}(\bar{x}) \right] / t$$

for all  $i, j = 1, \dots, n$ . If  $i = j$ , then the derivative is generally denoted by  $\partial^2 f(\bar{x}) / \partial x_i^2$ . For  $n = 1$  there exists a unique second-order directional derivative which coincides with the (usual) second-order derivative and it is also denoted by  $f''(\bar{x})$ .

**Example 1.11.** Take the function of Example 1.7:

$$\begin{aligned} \frac{\partial f}{\partial x_1}(x) &= \pi x_2 \cos(\pi x_1 x_2), & \frac{\partial f}{\partial x_2}(\bar{x}) &= \pi x_1 \cos(\pi x_1 x_2), \\ \frac{\partial^2 f}{\partial x_2 \partial x_1}(x) &= \pi \cos(\pi x_1 x_2) - \pi^2 x_1 x_2 \sin(\pi x_1 x_2) = \frac{\partial^2 f}{\partial x_1 \partial x_2}(x) \\ \frac{\partial^2 f}{\partial x_1^2}(x) &= -\pi^2 x_2^2 \sin(\pi x_1 x_2), & \frac{\partial^2 f}{\partial x_2^2}(x) &= -\pi^2 x_1^2 \sin(\pi x_1 x_2). \end{aligned}$$

**Theorem 1.7. (Schwarz)** Let  $\bar{x} \in \mathbb{R}^n$  and suppose  $f$  has the second-order partial derivatives  $\partial^2 f / \partial x_i \partial x_j$  and  $\partial^2 f / \partial x_j \partial x_i$  at each  $x \in B(\bar{x}, \varepsilon)$  for some  $\varepsilon > 0$ . If both the derivatives are continuous at  $\bar{x}$ , then

$$\frac{\partial^2 f}{\partial x_i \partial x_j}(\bar{x}) = \frac{\partial^2 f}{\partial x_j \partial x_i}(\bar{x}).$$

**Definition 1.16.** If  $f$  has second-order partial derivatives at  $\bar{x} \in \mathbb{R}^n$ , then

$$\nabla^2 f(\bar{x}) = \begin{bmatrix} \frac{\partial^2 f}{\partial x_1^2}(\bar{x}) & \cdots & \frac{\partial f}{\partial x_1 \partial x_n}(\bar{x}) \\ \vdots & \ddots & \vdots \\ \frac{\partial f}{\partial x_n \partial x_1}(\bar{x}) & \cdots & \frac{\partial^2 f}{\partial x_n^2}(\bar{x}) \end{bmatrix} \in \mathbb{R}^{n \times n}$$

is called the *Hessian matrix* of  $f$  at  $\bar{x}$ .

**Definition 1.17.**  $f$  is called *twice continuously differentiable* at  $\bar{x} \in \mathbb{R}^n$  if it has second-order partial derivatives at each  $x \in B(\bar{x}, \varepsilon)$  for some  $\varepsilon > 0$  and they are continuous at  $\bar{x}$ .  $f$  is twice continuously differentiable on a set  $D \subseteq \mathbb{R}^n$  if it is twice continuously differentiable at every  $x \in D$ .

Notice that the Hessian matrix of a twice continuously differentiable function is symmetric and therefore all its eigenvalues are real numbers.

**Theorem 1.8. (Taylor's formulas)** Suppose  $f$  is twice continuously differentiable (on  $\mathbb{R}^n$ ). The following statements hold for any  $\bar{x} \in \mathbb{R}^n$ :

- (i)  $\forall v \in \mathbb{R}^n \exists t \in ]0, 1[$  such that  $f(\bar{x} + v) = f(\bar{x}) + \nabla f(\bar{x})^T v + \frac{1}{2} v^T \nabla^2 f(\bar{x} + tv) v$ ;
- (ii)  $\forall v \in \mathbb{R}^n : f(\bar{x} + v) = f(\bar{x}) + \nabla f(\bar{x})^T v + \frac{1}{2} v^T \nabla^2 f(\bar{x}) v + r(v)$   
for some residual function  $r$  such that  $r(v)/\|v\|_2^2 \rightarrow 0$  as  $\|v\|_2 \rightarrow 0$ .

**Definition 1.18.**  $f$  is called *quadratic* if there exist  $Q \in \mathbb{R}^{n \times n}$ ,  $b \in \mathbb{R}^n$  and  $c \in \mathbb{R}$  such that

$$f(x) = \frac{1}{2} x^T Q x + b^T x + c = \frac{1}{2} \sum_{k=1}^{\ell} \sum_{\ell=1}^n q_{k\ell} x_k x_\ell + \sum_{k=1}^n b_k x_k + c.$$

Without loss of generality,  $Q$  can be taken symmetric, eventually replacing it by  $(Q + Q^T)/2$  since  $q_{k\ell} x_k x_\ell + q_{\ell k} x_\ell x_k = (q_{k\ell} + q_{\ell k}) x_k x_\ell / 2 + (q_{k\ell} - q_{\ell k}) x_\ell x_k / 2$ .

The partial derivatives of a quadratic function can be easily computed:

$$\begin{aligned} \frac{\partial f}{\partial x_i}(x) &= \frac{1}{2} \left( \sum_{\ell=1}^n q_{i\ell} x_\ell + \sum_{k=1}^n q_{ki} x_k \right) + b_i = \left( \sum_{\ell=1}^n q_{i\ell} x_\ell \right) + b_i = (Qx)_i + b_i \\ \frac{\partial^2 f}{\partial x_j \partial x_i}(x) &= \frac{\partial}{\partial x_j} \left( \frac{\partial f}{\partial x_i} \right)(x) = \frac{\partial f}{\partial x_j} \left( \sum_{\ell=1}^n q_{i\ell} x_\ell + b_i \right) = q_{ij}. \end{aligned}$$

Therefore,  $\nabla f(x) = Qx + b$  and  $\nabla^2 f(x) = Q$ .

Considering any  $v = x - \bar{x} \approx 0$ , the second-order Taylor's formula states that  $f(x)$  can be approximated by a quadratic function, namely  $f(x) \approx q(x)$  with

$$q(x) = f(\bar{x}) + \nabla f(\bar{x})^T (x - \bar{x}) + \frac{1}{2} (x - \bar{x})^T \nabla^2 f(\bar{x}) (x - \bar{x}),$$

that is

$$q(x) = \frac{1}{2}x^T \nabla^2 f(\bar{x})x + (\nabla f(\bar{x}) - \nabla^2 f(\bar{x})\bar{x})^T x + (f(\bar{x}) - \nabla f(\bar{x})^T \bar{x} + \frac{1}{2}\bar{x}^T \nabla^2 f(\bar{x})\bar{x}).$$

**Example 1.12.** Take  $n = 2$  and  $f(x_1, x_2) = -x_1^4 - x_2^2$ :

$$\nabla f(x) = \begin{pmatrix} -4x_1^3 \\ -2x_2 \end{pmatrix}, \quad \nabla^2 f(x) = \begin{bmatrix} -12x_1^2 & 0 \\ 0 & -2 \end{bmatrix}.$$

Considering  $\bar{x} = (0, -2/5)$  the quadratic approximation of  $f(x)$  near  $\bar{x}$  is given by

$$q(x) = -2x_2^2 - 12x_2/5 - 20/25.$$