

Chapter 1. Multivariate differential calculus

1.2 The total differential

in general not a perfect field

Definition: Let $D \subset \mathbb{R}^n$ open, $\mathbf{x}^0 \in D$ and $\mathbf{f} : D \rightarrow \mathbb{R}^m$. The function $\mathbf{f}(\mathbf{x})$ is called **differentiable** in \mathbf{x}^0 (or **totally differentiable** in \mathbf{x}_0), if there exists a linear map

$$l(\mathbf{x}, \mathbf{x}^0) := \mathbf{A} \cdot (\mathbf{x} - \mathbf{x}^0)$$

with a matrix $\mathbf{A} \in \mathbb{R}^{m \times n}$ which satisfies the following approximation property

$$\mathbf{f}(\mathbf{x}) = \mathbf{f}(\mathbf{x}^0) + \mathbf{A} \cdot (\mathbf{x} - \mathbf{x}^0) + o(\|\mathbf{x} - \mathbf{x}^0\|)$$

i.e.

$$\lim_{\mathbf{x} \rightarrow \mathbf{x}^0} \frac{\mathbf{f}(\mathbf{x}) - \mathbf{f}(\mathbf{x}^0) - \mathbf{A} \cdot (\mathbf{x} - \mathbf{x}^0)}{\|\mathbf{x} - \mathbf{x}^0\|} = 0.$$

The total differential and the Jacobian matrix.

Notation: We call the linear map \mathbf{l} the differential or the total differential of $\mathbf{f}(\mathbf{x})$ at the point \mathbf{x}^0 . We denote \mathbf{l} by $\mathbf{df}(\mathbf{x}^0)$.

The related matrix \mathbf{A} is called Jacobi-matrix of $\mathbf{f}(\mathbf{x})$ at the point \mathbf{x}^0 and is denoted by $\mathbf{Jf}(\mathbf{x}^0)$ (or $\mathbf{Df}(\mathbf{x}^0)$ or $\mathbf{f}'(\mathbf{x}^0)$).

Remark: For $m = n = 1$ we obtain the well known relation

$$f(x) = f(x_0) + \underbrace{f'(x_0)}_{\substack{\mathbf{A} \quad (1 \times 1)}}(x - x_0) + o(|x - x_0|)$$

for the derivative $f'(x_0)$ at the point x_0 .

Remark: In case of a scalar function ($m = 1$) the matrix $\mathbf{A} = \mathbf{a}$ is a row vector and $\mathbf{a}(\mathbf{x} - \mathbf{x}^0)$ a scalar product $\langle \mathbf{a}^T, \mathbf{x} - \mathbf{x}^0 \rangle$.

$n=2, m=1$

$$f(x_1, x_2) = f(x_1^0, x_2^0) + \frac{\partial f}{\partial x_1}(x_1^0, x_2^0)(x_1 - x_1^0) + \frac{\partial f}{\partial x_2}(x_1^0, x_2^0)(x_2 - x_2^0) + \dots = f(x_1^0, x_2^0) + \underbrace{\left(\frac{\partial f}{\partial x_1}(x_1^0, x_2^0), \frac{\partial f}{\partial x_2}(x_1^0, x_2^0) \right)}_{\substack{\mathbf{A} \\ 1 \times 2}} \cdot \underbrace{\begin{pmatrix} x_1 - x_1^0 \\ x_2 - x_2^0 \end{pmatrix}}_{\substack{\mathbf{x} - \mathbf{x}^0 \\ 2 \times 1}} + \dots$$

Total and partial differentiability.

Theorem: Let $\mathbf{f} : D \rightarrow \mathbb{R}^m$, $\mathbf{x}^0 \in D \subset \mathbb{R}^n$, D open.

- a) If $\mathbf{f}(\mathbf{x})$ is differentiable in \mathbf{x}^0 , then $\mathbf{f}(\mathbf{x})$ is continuous in \mathbf{x}^0 .
- b) If $\mathbf{f}(\mathbf{x})$ is differentiable in \mathbf{x}^0 , then the (total) differential and thus the Jacobi-matrix are uniquely determined and we have

$$\overset{m \times n}{\mathbf{J} \mathbf{f}(\mathbf{x}^0)} = \begin{pmatrix} \frac{\partial f_1}{\partial x_1}(\mathbf{x}^0) & \dots & \frac{\partial f_1}{\partial x_n}(\mathbf{x}^0) \\ \vdots & & \vdots \\ \frac{\partial f_m}{\partial x_1}(\mathbf{x}^0) & \dots & \frac{\partial f_m}{\partial x_n}(\mathbf{x}^0) \end{pmatrix} = \begin{pmatrix} Df_1(\mathbf{x}^0) \\ \vdots \\ Df_m(\mathbf{x}^0) \end{pmatrix}$$

$\underbrace{\frac{\partial f_1}{\partial x_1}(\mathbf{x}^0) \quad \dots \quad \frac{\partial f_1}{\partial x_n}(\mathbf{x}^0)}_{\frac{\partial \mathbf{f}}{\partial x_1}(\mathbf{x}^0)} \quad \dots \quad \underbrace{\frac{\partial f_m}{\partial x_1}(\mathbf{x}^0) \quad \dots \quad \frac{\partial f_m}{\partial x_n}(\mathbf{x}^0)}_{\frac{\partial \mathbf{f}}{\partial x_n}(\mathbf{x}^0)}$

- c) If $\mathbf{f}(\mathbf{x})$ is a \mathcal{C}^1 -function on D , then $\mathbf{f}(\mathbf{x})$ is differentiable on D .

Proof of a).

If \mathbf{f} is differentiable in \mathbf{x}^0 , then by definition

$$\lim_{\mathbf{x} \rightarrow \mathbf{x}^0} \frac{\mathbf{f}(\mathbf{x}) - \mathbf{f}(\mathbf{x}^0) - \mathbf{A} \cdot (\mathbf{x} - \mathbf{x}^0)}{\|\mathbf{x} - \mathbf{x}^0\|} = 0$$

Thus we conclude

$$\lim_{\mathbf{x} \rightarrow \mathbf{x}^0} \underbrace{\|\mathbf{f}(\mathbf{x}) - \mathbf{f}(\mathbf{x}^0) - \mathbf{A} \cdot (\mathbf{x} - \mathbf{x}^0)\|}_{\rightarrow 0} = 0$$

and we obtain

$$\begin{aligned} \|\mathbf{f}(\mathbf{x}) - \mathbf{f}(\mathbf{x}^0)\| &\leq \underbrace{\|\mathbf{f}(\mathbf{x}) - \mathbf{f}(\mathbf{x}^0) - \mathbf{A} \cdot (\mathbf{x} - \mathbf{x}^0)\|}_{\rightarrow 0} + \underbrace{\|\mathbf{A} \cdot (\mathbf{x} - \mathbf{x}^0)\|}_{\|\mathbf{A}\| \|\mathbf{x} - \mathbf{x}^0\| \rightarrow 0} \\ &\rightarrow 0 \quad \text{as } \mathbf{x} \rightarrow \mathbf{x}^0 \end{aligned}$$

Therefore the function \mathbf{f} is continuous at \mathbf{x}^0 .

Proof of b).

Let $\mathbf{x} = \mathbf{x}^0 + t\mathbf{e}_i$, $|t| < \varepsilon$, $i \in \{1, \dots, n\}$. Since \mathbf{f} is differentiable at \mathbf{x}^0 , we have

$$\lim_{\mathbf{x} \rightarrow \mathbf{x}^0} \frac{\mathbf{f}(\mathbf{x}) - \mathbf{f}(\mathbf{x}^0) - \mathbf{A} \cdot (\mathbf{x} - \mathbf{x}^0)}{\|\mathbf{x} - \mathbf{x}^0\|_\infty} = 0$$

We write $\mathbf{x} - \mathbf{x}^0 = t\mathbf{e}_i$ $\|\mathbf{x} - \mathbf{x}^0\|_\infty = |t|$

$$\begin{aligned} \frac{\mathbf{f}(\mathbf{x}) - \mathbf{f}(\mathbf{x}^0) - \mathbf{A} \cdot (\mathbf{x} - \mathbf{x}^0)}{\|\mathbf{x} - \mathbf{x}^0\|_\infty} &= \frac{\mathbf{f}(\mathbf{x}^0 + t\mathbf{e}_i) - \mathbf{f}(\mathbf{x}^0) - t\mathbf{A}\mathbf{e}_i}{|t|} \\ &\rightarrow 0 \\ &= \frac{t}{|t|} \cdot \left(\frac{\mathbf{f}(\mathbf{x}^0 + t\mathbf{e}_i) - \mathbf{f}(\mathbf{x}^0)}{t} - \mathbf{A}\mathbf{e}_i \right) \\ &\rightarrow 0 \quad \text{as } t \rightarrow 0 \end{aligned}$$

Thus

$$\lim_{t \rightarrow 0} \frac{\frac{\partial \mathbf{f}}{\partial x_i}(\mathbf{x}^0 + t\mathbf{e}_i) - \mathbf{f}(\mathbf{x}^0)}{t} = \mathbf{A}\mathbf{e}_i \quad i = 1, \dots, n$$

i column of A

Examples.

- Consider the scalar function $f(x_1, x_2) = x_1 e^{2x_2}$. Then the Jacobian is given by: $n=2$
 $m=1$

$$\text{J}f(x_1, x_2) = Df(x_1, x_2) = e^{2x_2}(1, 2x_1) = \left(\frac{\partial f}{\partial x_1}, \frac{\partial f}{\partial x_2} \right)$$

- Consider the function $\mathbf{f} : \mathbb{R}^3 \rightarrow \mathbb{R}^2$ defined by

$$\mathbf{f}(x_1, x_2, x_3) = \begin{pmatrix} x_1 x_2 x_3 \\ \sin(x_1 + 2x_2 + 3x_3) \end{pmatrix}$$

The Jacobian is given by

$$\mathbf{J}\mathbf{f}(x_1, x_2, x_3) = \begin{pmatrix} \frac{\partial f_1}{\partial x_1} & \frac{\partial f_1}{\partial x_2} & \frac{\partial f_1}{\partial x_3} \\ \frac{\partial f_2}{\partial x_1} & \frac{\partial f_2}{\partial x_2} & \frac{\partial f_2}{\partial x_3} \end{pmatrix} = \begin{pmatrix} x_2 x_3 & x_1 x_3 & x_1 x_2 \\ \cos(s) & 2 \cos(s) & 3 \cos(s) \end{pmatrix}$$

with $s = x_1 + 2x_2 + 3x_3$.

Further examples.

- Let $f(\mathbf{x}) = \mathbf{Ax}$, $\mathbf{A} \in \mathbb{R}^{m \times n}$ and $\mathbf{x} \in \mathbb{R}^n$. Then

$$f(\mathbf{x}) = \mathbf{Ax} = \begin{pmatrix} a_{11}x_1 + a_{12}x_2 + \dots \\ a_{m1}x_1 + \dots \end{pmatrix}$$

$$\mathbf{J}f(\mathbf{x}) = \mathbf{A} \quad \text{for all } \mathbf{x} \in \mathbb{R}^n$$

- Let $f(\mathbf{x}) = \mathbf{x}^T \mathbf{Ax} = \langle \mathbf{x}, \mathbf{Ax} \rangle$, $\mathbf{A} \in \mathbb{R}^{n \times n}$ and $\mathbf{x} \in \mathbb{R}^n$.
Then we have

$$f: \mathbb{R}^n \rightarrow \mathbb{R}$$

$$\mathbf{J}f \quad 1 \times n$$

$$\frac{\partial x}{\partial x_i} = e_i$$

$$\underbrace{\frac{\partial f}{\partial x_i}}_{\substack{\text{ith column of} \\ \mathbf{J}f}} = \langle e_i, \mathbf{Ax} \rangle + \langle \mathbf{x}, \mathbf{A}e_i \rangle$$

$$e_i^T \mathbf{Ax} = (e_i^T \mathbf{Ax})^T = \mathbf{x}^T \mathbf{A}^T e_i$$

$$= e_i^T \mathbf{Ax} + \mathbf{x}^T \mathbf{A}e_i$$

$$= \mathbf{x}^T (\mathbf{A}^T + \mathbf{A}) e_i$$

$$\underbrace{\mathbf{x}^T (\mathbf{A}^T + \mathbf{A})}_{\text{ith column of } \mathbf{x}^T (\mathbf{A}^T + \mathbf{A})}$$

We conclude

$$\mathbf{J}f(\mathbf{x}) = \text{grad} f(\mathbf{x}) = \mathbf{x}^T (\mathbf{A}^T + \mathbf{A})$$

Rules for the differentiation.

Theorem:

- a) **Linearität:** LET $\mathbf{f}, \mathbf{g} : D \rightarrow \mathbb{R}^m$ be differentiable in $\mathbf{x}^0 \in D$, D open. Then $\alpha \mathbf{f}(\mathbf{x}^0) + \beta \mathbf{g}(\mathbf{x}^0)$, and $\alpha, \beta \in \mathbb{R}$ are differentiable in \mathbf{x}^0 and we have

$$\mathbf{d}(\alpha \mathbf{f} + \beta \mathbf{g})(\mathbf{x}^0) = \alpha \mathbf{d}\mathbf{f}(\mathbf{x}^0) + \beta \mathbf{d}\mathbf{g}(\mathbf{x}^0)$$

$$\mathbf{J}(\alpha \mathbf{f} + \beta \mathbf{g})(\mathbf{x}^0) = \alpha \mathbf{J}\mathbf{f}(\mathbf{x}^0) + \beta \mathbf{J}\mathbf{g}(\mathbf{x}^0)$$

- b) **Chain rule:** Let $\mathbf{f} : D \rightarrow \mathbb{R}^m$ be differentiable in $\mathbf{x}^0 \in D$, D open. Let $\mathbf{g} : E \rightarrow \mathbb{R}^k$ be differentiable in $\mathbf{y}^0 = \mathbf{f}(\mathbf{x}^0) \in E \subset \mathbb{R}^m$, E open. Then $\mathbf{g} \circ \mathbf{f}$ is differentiable in \mathbf{x}^0 .

For the differentials it holds

$$\mathbf{d}(\mathbf{g} \circ \mathbf{f})(\mathbf{x}^0) = \mathbf{d}\mathbf{g}(\mathbf{y}^0) \circ \mathbf{d}\mathbf{f}(\mathbf{x}^0)$$

and analogously for the Jacobian matrix

$$\mathbf{J}(\mathbf{g} \circ \mathbf{f})(\mathbf{x}^0) = \mathbf{J}\mathbf{g}(\mathbf{y}^0) \cdot \mathbf{J}\mathbf{f}(\mathbf{x}^0)$$

$k \times n$ $k \times m$ $m \times n$

Examples for the chain rule.

Let $I \subset \mathbb{R}$ be an interval. Let $\mathbf{h} : I \rightarrow \mathbb{R}^n$ be a curve, differentiable in $t_0 \in I$ with values in $D \subset \mathbb{R}^n$, D open. Let $f : D \rightarrow \mathbb{R}$ be a scalar function, differentiable in $\mathbf{x}^0 = \mathbf{h}(t_0)$.

$$\begin{aligned} h &: \mathbb{R}^1 \rightarrow \mathbb{R}^n \\ f &: \mathbb{R}^n \rightarrow \mathbb{R}^1 \end{aligned} \quad f \circ h : \mathbb{R}^1 \rightarrow \mathbb{R}^1$$

Then the composition

$$(f \circ \mathbf{h})(t) = f(h_1(t), \dots, h_n(t))$$

is differentiable in t_0 and we have for the derivative:

$$\begin{aligned} (f \circ \mathbf{h})'(t_0) &= \underset{1 \times n}{\mathbf{J}f(\mathbf{h}(t_0))} \cdot \underset{n \times 1}{\mathbf{J}\mathbf{h}(t_0)} \\ &= \text{grad} f(\mathbf{h}(t_0)) \cdot \mathbf{h}'(t_0) \\ &= \sum_{k=1}^n \frac{\partial f}{\partial x_k}(\mathbf{h}(t_0)) \cdot h'_k(t_0) \end{aligned}$$