4.4 Derivatives in certain directions

Definition 38 Derivative in <u>certain</u> direction: If $f : \mathbb{R}^n \to \mathbb{R}$, direction \vec{n} , than

$$\frac{\partial f}{\partial \vec{n}} = \lim_{h \to 0} \frac{f(\vec{x} + h\vec{n}) - f(\vec{x})}{h}$$

is defined as the derivative of f in the direction \vec{n} \Rightarrow Thus partial derivative $\frac{\partial f}{\partial x_k}$ is derived in the direction $\vec{e_k}$

Example:



$$\begin{aligned} f(x_1, x_2) &= x_1^2 + x_2^3 \qquad \vec{n} = \binom{n_1}{n_2} \\ f(\vec{x} + h\vec{n}) &= (x_1 + hn_1)^2 + (x_2 + hn_2)^3 \\ f(\vec{x}) &= x_1^2 + x_2^3 \\ \rightarrow f(\vec{x} + h\vec{n}) - f(\vec{x}) &= x_1^2 + 2hn_1x_1 + h^2n_1^2 + x_2^3 + 3x_2^2hn_2 + 3x_2h^2n_2^2 + h^3n_2^3 - (x_1^2 + x_2^3) \\ \rightarrow \frac{\partial f}{\partial \vec{n}} &= \lim_{h \to 0} \frac{2hn_1x_1 + h^2n_1^2 + 3x_2^2hn_2 + 3x_2h^2n_2^2}{h} = 2n_1x_1 + 3x_2^2n_2 \\ &= \binom{2x_1}{3x_2^2} \cdot \binom{n_1}{n_2} = \binom{\frac{\partial f}{\partial x_1}}{\frac{\partial f}{\partial x_2}} \cdot \vec{n} \end{aligned}$$

In general: writing \vec{n} as a linear combination of base vectors, i.e.

$$\vec{n} = \sum n_i \vec{e_i}$$

and taking into account, that differentiation is a linear operation we get

$$\frac{\partial f}{\partial \vec{n}} = \sum \frac{\partial f}{\partial \vec{e_i}} n_i = \begin{pmatrix} \frac{\partial f}{\partial x_1} \\ \vdots \\ \frac{\partial f}{\partial x_N} \end{pmatrix} \qquad \cdot \begin{pmatrix} n_1 \\ \vdots \\ n_N \end{pmatrix}$$

This vector is called the gradient of f

Definition 39 $f : \mathbb{R}^N \to \mathbb{R}$ then gradient is the vector

$$\vec{\nabla}f = \begin{pmatrix} \frac{\partial f}{\partial x_1} \\ \vdots \\ \frac{\partial f}{\partial x_N} \end{pmatrix} \in \mathbb{R}^N$$

Example:

$$f(\vec{x}) = \sqrt{x_1^2 + \ldots + x_N^2} \qquad \frac{\partial f}{\partial x_k} = \frac{x_k}{\sqrt{x_1^2 + \ldots + x_N^2}}$$
$$\rightarrow \vec{\nabla} f = \frac{1}{\sqrt{x_1^2 + \ldots + x_n^2}} \begin{pmatrix} x_1 \\ \vdots \\ x_k \end{pmatrix} = \frac{1}{|\vec{r}|} \vec{r}$$

Derivative in a certain direction $\vec{n} \in \mathbb{R}^N$ can be written as:

$$\frac{\partial f}{\partial \vec{n}} = \vec{\nabla} f \cdot \vec{n}$$

Thus as illustrated in the figure, the gradient is the direction of steepest descent.



Higher order partial derivatives: function: $f : \mathbb{R}^N \to \mathbb{R}$ $f(x_1, \ldots, x_N)$ partial derivative $\frac{\partial f}{\partial x_k}$ is again a function of x_1, \ldots, x_N second partial derivative:

$$\frac{\partial}{\partial x_k} \left(\frac{\partial f}{\partial x_k} \right) = \frac{\partial^2 f}{\partial x_k^2}$$

Also possible:

$$\frac{\partial}{\partial x_j} \left(\frac{\partial f}{\partial x_k} \right) = \frac{\partial^2 f}{\partial x_j \partial x_k}$$

Always (apart from mathematically pathological cases):

 $\frac{\partial^2 f}{\partial x_j \partial x_k} = \frac{\partial^2 f}{\partial x_k \partial x_j} \leftarrow \text{ exchange order of derivatives doesn't influence the result}$

n-th derivative:

$$\underbrace{\frac{\partial^n f}{\partial x_k \dots \partial x_j}}_{n-\text{terms}}$$

Examples:

(i)

$$f(x_1, x_2) = x_1^2 + x_2^3$$
$$\frac{\partial f}{\partial x_1} = 2x_1 , \quad \frac{\partial f}{\partial x_2} = 3x_2^2$$
$$\frac{\partial^2 f}{\partial x_1^2} = 2 , \quad \frac{\partial^2 f}{\partial x_2^2} = 6x_2$$
$$\frac{\partial^2 f}{\partial x_1 \partial x_2} = 0 = \frac{\partial^2 f}{\partial x_2 \partial x_1}$$

(ii)

$$f(x,y) = e^{x^2}y^3$$

$$\frac{\partial f}{\partial x} = 2xe^{x^2}y^3 \qquad \frac{\partial f}{\partial y} = 3y^2e^{x^2}$$

$$\frac{\partial^2 f}{\partial x^2} = 2e^{x^2}y^3(1+2x^2) \qquad \frac{\partial^2 f}{\partial y^2} = 6ye^{x^2}$$

$$\frac{\partial^2 f}{\partial x \partial y} = 6xy^2e^{x^2} \qquad \frac{\partial^2 f}{\partial y \partial x} = 6xy^2e^{x^2}$$

$$\frac{\partial^3 f}{\partial y \partial x^2} = 6y^2e^{x^2}(1+2x^2)$$