



University of Cyprus
MAI613 - Research Methodologies and Professional
Practices in AI
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Exercises on Vector Calculus

Exercises

Solve Exercises 5.1, 5.3, 5.4, 5.7, 5.8, and 5.9 from the book:

- M.P. Deisenroth, A. A. Faisal, and C. S. Ong, “Mathematics for Machine Learning,” Cambridge University Press, 2020.

<https://mml-book.github.io/book/mml-book.pdf>

Note: These exercises are intended for self-assessment purposes. Their solutions will be uploaded in one week from now.

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Vector Calculus

Exercises

5.1 Compute the derivative $f'(x)$ for

$$f(x) = \log(x^4) \sin(x^3) .$$

$$f'(x) = \frac{4}{x} \sin(x^3) + 12x^2 \log(x) \cos(x^3)$$

5.3 Compute the derivative $f'(x)$ of the function

$$f(x) = \exp\left(-\frac{1}{2\sigma^2}(x - \mu)^2\right),$$

where $\mu, \sigma \in \mathbb{R}$ are constants.

$$f'(x) = -\frac{1}{\sigma^2}f(x)(x - \mu)$$

5.4 Compute the Taylor polynomials T_n , $n = 0, \dots, 5$ of $f(x) = \sin(x) + \cos(x)$ at $x_0 = 0$.

$$T_0(x) = 1$$

$$T_1(x) = T_0(x) + x$$

$$T_2(x) = T_1(x) - \frac{x^2}{2}$$

$$T_3(x) = T_2(x) - \frac{x^3}{6}$$

$$T_4(x) = T_3(x) + \frac{x^4}{24}$$

$$T_5(x) = T_4(x) + \frac{x^5}{120}$$

5.7 Compute the derivatives $df/d\mathbf{x}$ of the following functions by using the chain rule. Provide the dimensions of every single partial derivative. Describe your steps in detail.

a.

$$f(z) = \log(1 + z), \quad z = \mathbf{x}^\top \mathbf{x}, \quad \mathbf{x} \in \mathbb{R}^D$$

b.

$$f(\mathbf{z}) = \sin(\mathbf{z}), \quad \mathbf{z} = \mathbf{A}\mathbf{x} + \mathbf{b}, \quad \mathbf{A} \in \mathbb{R}^{E \times D}, \mathbf{x} \in \mathbb{R}^D, \mathbf{b} \in \mathbb{R}^E$$

where $\sin(\cdot)$ is applied to every element of \mathbf{z} .

a.

$$\begin{aligned}\frac{df}{d\mathbf{x}} &= \underbrace{\frac{\partial f}{\partial \mathbf{z}}}_{\in \mathbb{R}} \underbrace{\frac{\partial \mathbf{z}}{\partial \mathbf{x}}}_{\in \mathbb{R}^{1 \times D}} \in \mathbb{R}^{1 \times D} \\ \frac{\partial f}{\partial z} &= \frac{1}{1+z} = \frac{1}{1+\mathbf{x}^\top \mathbf{x}} \\ \frac{\partial \mathbf{z}}{\partial \mathbf{x}} &= 2\mathbf{x}^\top \\ \implies \frac{df}{d\mathbf{x}} &= \frac{2\mathbf{x}^\top}{1+\mathbf{x}^\top \mathbf{x}}\end{aligned}$$

b.

$$\begin{aligned}\frac{df}{d\mathbf{x}} &= \underbrace{\frac{\partial f}{\partial \mathbf{z}}}_{\in \mathbb{R}^{E \times E}} \underbrace{\frac{\partial \mathbf{z}}{\partial \mathbf{x}}}_{\in \mathbb{R}^{E \times D}} \in \mathbb{R}^{E \times D} \\ \sin(\mathbf{z}) &= \begin{bmatrix} \sin z_1 \\ \vdots \\ \sin z_E \end{bmatrix} \\ \frac{\partial \sin \mathbf{z}}{\partial z_i} &= \begin{bmatrix} 0 \\ \vdots \\ 0 \\ \cos(z_i) \\ 0 \\ \vdots \\ 0 \end{bmatrix} \in \mathbb{R}^E \\ \implies \frac{\partial f}{\partial \mathbf{z}} &= \text{diag}(\cos(\mathbf{z})) \in \mathbb{R}^{E \times E} \\ \frac{\partial \mathbf{z}}{\partial \mathbf{x}} &= \mathbf{A} \in \mathbb{R}^{E \times D} : \\ c_i &= \sum_{j=1}^D A_{ij} x_j \implies \frac{\partial c_i}{\partial x_j} = A_{ij}, \quad i = 1, \dots, E, j = 1, \dots, D\end{aligned}$$

Here, we defined c_i to be the i th component of \mathbf{Ax} . The offset \mathbf{b} is constant and vanishes when taking the gradient with respect to \mathbf{x} . Overall, we obtain

$$\frac{df}{d\mathbf{x}} = \text{diag}(\cos(\mathbf{Ax} + \mathbf{b}))\mathbf{A}$$

5.8 Compute the derivatives $df/d\mathbf{x}$ of the following functions. Describe your steps in detail.

a. Use the chain rule. Provide the dimensions of every single partial derivative.

$$\begin{aligned}f(z) &= \exp(-\tfrac{1}{2}z) \\ z &= g(\mathbf{y}) = \mathbf{y}^\top \mathbf{S}^{-1} \mathbf{y} \\ \mathbf{y} &= h(\mathbf{x}) = \mathbf{x} - \boldsymbol{\mu}\end{aligned}$$

where $\mathbf{x}, \boldsymbol{\mu} \in \mathbb{R}^D$, $\mathbf{S} \in \mathbb{R}^{D \times D}$.

The desired derivative can be computed using the chain rule:

$$\frac{df}{d\mathbf{x}} = \underbrace{\frac{\partial f}{\partial \mathbf{z}}}_{1 \times 1} \underbrace{\frac{\partial \mathbf{g}}{\partial \mathbf{y}}}_{1 \times D} \underbrace{\frac{\partial h}{\partial \mathbf{x}}}_{D \times D} \in \mathbb{R}^{1 \times D}$$

Here

$$\begin{aligned}\frac{\partial f}{\partial z} &= -\frac{1}{2} \exp(-\frac{1}{2}z) \\ \frac{\partial \mathbf{g}}{\partial \mathbf{y}} &= 2\mathbf{y}^\top \mathbf{S}^{-1} \\ \frac{\partial h}{\partial \mathbf{x}} &= \mathbf{I}_D\end{aligned}$$

so that

$$\frac{df}{d\mathbf{x}} = -\exp\left(-\frac{1}{2}(\mathbf{x} - \boldsymbol{\mu})^\top \mathbf{S}^{-1}(\mathbf{x} - \boldsymbol{\mu})\right)(\mathbf{x} - \boldsymbol{\mu})^\top \mathbf{S}^{-1}$$

b.

$$f(\mathbf{x}) = \text{tr}(\mathbf{x}\mathbf{x}^\top + \sigma^2 \mathbf{I}), \quad \mathbf{x} \in \mathbb{R}^D$$

Here $\text{tr}(\mathbf{A})$ is the trace of \mathbf{A} , i.e., the sum of the diagonal elements A_{ii} .

Hint: Explicitly write out the outer product.

Let us have a look at the outer product. We define $\mathbf{X} = \mathbf{x}\mathbf{x}^\top$ with

$$X_{ij} = x_i x_j$$

The trace sums up all the diagonal elements, such that

$$\frac{\partial}{\partial x_j} \text{tr}(\mathbf{X} + \sigma^2 \mathbf{I}) = \sum_{i=1}^D \frac{\partial X_{ii} + \sigma^2}{\partial x_j} = 2x_j$$

for $j = 1, \dots, D$. Overall, we get

$$\frac{\partial}{\partial \mathbf{x}} \text{tr}(\mathbf{x}\mathbf{x}^\top + \sigma^2 \mathbf{I}) = 2\mathbf{x}^\top \in \mathbb{R}^{1 \times D}$$

- c. Use the chain rule. Provide the dimensions of every single partial derivative. You do not need to compute the product of the partial derivatives explicitly.

$$\mathbf{f} = \tanh(\mathbf{z}) \in \mathbb{R}^M$$

$$\mathbf{z} = \mathbf{A}\mathbf{x} + \mathbf{b}, \quad \mathbf{x} \in \mathbb{R}^N, \mathbf{A} \in \mathbb{R}^{M \times N}, \mathbf{b} \in \mathbb{R}^M.$$

Here, \tanh is applied to every component of \mathbf{z} .

$$\begin{aligned}\frac{\partial \mathbf{f}}{\partial \mathbf{z}} &= \text{diag}(1 - \tanh^2(\mathbf{z})) \in \mathbb{R}^{M \times M} \\ \frac{\partial \mathbf{z}}{\partial \mathbf{x}} &= \frac{\partial \mathbf{A}\mathbf{x}}{\partial \mathbf{x}} = \mathbf{A} \in \mathbb{R}^{M \times N}\end{aligned}$$

We get the latter result by defining $\mathbf{y} = \mathbf{Ax}$, such that

$$\begin{aligned} y_i = \sum_j A_{ij}x_j &\implies \frac{\partial y_i}{\partial x_k} = A_{ik} \implies \frac{\partial y_i}{\partial \mathbf{x}} = [A_{i1}, \dots, A_{iN}] \in \mathbb{R}^{1 \times N} \\ &\implies \frac{\partial \mathbf{y}}{\partial \mathbf{x}} = \mathbf{A} \end{aligned}$$

The overall derivative is an $M \times N$ matrix.

5.9 We define

$$\begin{aligned} g(\mathbf{z}, \boldsymbol{\nu}) &:= \log p(\mathbf{x}, \mathbf{z}) - \log q(\mathbf{z}, \boldsymbol{\nu}) \\ \mathbf{z} &:= t(\boldsymbol{\epsilon}, \boldsymbol{\nu}) \end{aligned}$$

for differentiable functions p, q, t . By using the chain rule, compute the gradient

$$\frac{d}{d\boldsymbol{\nu}} g(\mathbf{z}, \boldsymbol{\nu}).$$

$$\begin{aligned} \frac{d}{d\boldsymbol{\nu}} g(\mathbf{z}, \boldsymbol{\nu}) &= \frac{d}{d\boldsymbol{\nu}} (\log p(\mathbf{x}, \mathbf{z}) - \log q(\mathbf{z}, \boldsymbol{\nu})) = \frac{d}{d\boldsymbol{\nu}} \log p(\mathbf{x}, \mathbf{z}) - \frac{d}{d\boldsymbol{\nu}} \log q(\mathbf{z}, \boldsymbol{\nu}) \\ &= \frac{\partial}{\partial \mathbf{z}} \log p(\mathbf{x}, \mathbf{z}) \frac{\partial t(\boldsymbol{\epsilon}, \boldsymbol{\nu})}{\partial \boldsymbol{\nu}} - \frac{\partial}{\partial \mathbf{z}} \log q(\mathbf{z}, \boldsymbol{\nu}) \frac{\partial t(\boldsymbol{\epsilon}, \boldsymbol{\nu})}{\partial \boldsymbol{\nu}} - \frac{\partial}{\partial \boldsymbol{\nu}} \log q(\mathbf{z}, \boldsymbol{\nu}) \\ &= \left(\frac{\partial}{\partial \mathbf{z}} \log p(\mathbf{x}, \mathbf{z}) - \frac{\partial}{\partial \mathbf{z}} \log q(\mathbf{z}, \boldsymbol{\nu}) \right) \frac{\partial t(\boldsymbol{\epsilon}, \boldsymbol{\nu})}{\partial \boldsymbol{\nu}} - \frac{\partial}{\partial \boldsymbol{\nu}} \log q(\mathbf{z}, \boldsymbol{\nu}) \\ &= \left(\frac{1}{p(\mathbf{x}, \mathbf{z})} \frac{\partial}{\partial \mathbf{z}} p(\mathbf{x}, \mathbf{z}) - \frac{1}{q(\mathbf{z}, \boldsymbol{\nu})} \frac{\partial}{\partial \mathbf{z}} q(\mathbf{z}, \boldsymbol{\nu}) \right) \frac{\partial t(\boldsymbol{\epsilon}, \boldsymbol{\nu})}{\partial \boldsymbol{\nu}} - \frac{\partial}{\partial \boldsymbol{\nu}} \log q(\mathbf{z}, \boldsymbol{\nu}) \end{aligned}$$