

Matrix Differentiation

CS4243 Computer Vision and Pattern Recognition

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Matrix Differentiation

This set of slides summarizes some commonly used matrix differentiation formulae.

In the following,

- \mathbf{A} and \mathbf{B} are $n \times n$ matrices

$$\mathbf{A} = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{bmatrix}, \quad \mathbf{B} = \begin{bmatrix} b_{11} & \cdots & b_{1n} \\ \vdots & \ddots & \vdots \\ b_{n1} & \cdots & b_{nn} \end{bmatrix}. \quad (1)$$

- \mathbf{x} and \mathbf{y} are $n \times 1$ column matrices (i.e., vectors)

$$\mathbf{x} = \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix}, \quad \mathbf{y} = \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix}. \quad (2)$$

$$(1) \ E = \mathbf{x}^\top \mathbf{x}$$

$$E = \mathbf{x}^\top \mathbf{x} = \sum_i x_i^2 = x_1^2 + \cdots + x_n^2. \quad (3)$$

$$\frac{\partial E}{\partial x_i} = 2x_i. \quad (4)$$

So,

$$\frac{\partial E}{\partial \mathbf{x}} = \begin{bmatrix} \partial E / \partial x_1 \\ \vdots \\ \partial E / \partial x_n \end{bmatrix} = 2 \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} = 2 \mathbf{x}. \quad (5)$$

$$(2) \quad E = \mathbf{x}^\top \mathbf{y}$$

$$E = \mathbf{x}^\top \mathbf{y} = x_1 y_1 + \cdots + x_n y_n. \quad (6)$$

$$\frac{\partial E}{\partial x_i} = y_i. \quad (7)$$

So,

$$\frac{\partial E}{\partial \mathbf{x}} = \mathbf{y}. \quad (8)$$

$$(3) \ E = (\mathbf{x}^\top \mathbf{y})^2$$

$$E = (\mathbf{x}^\top \mathbf{y})^2 = (x_1 y_1 + \cdots + x_n y_n)^2. \quad (9)$$

$$\frac{\partial E}{\partial x_i} = 2(x_1 y_1 + \cdots + x_n y_n) y_i. \quad (10)$$

So,

$$\frac{\partial E}{\partial \mathbf{x}} = \begin{bmatrix} \frac{\partial E}{\partial x_1} \\ \vdots \\ \frac{\partial E}{\partial x_n} \end{bmatrix} = 2 \mathbf{x}^\top \mathbf{y} \mathbf{y}. \quad (11)$$

(4) \mathbf{Ax}

$$\mathbf{Ax} = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{bmatrix} \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} = \begin{bmatrix} a_{11}x_1 + \cdots + a_{1n}x_n \\ \vdots \\ a_{n1}x_1 + \cdots + a_{nn}x_n \end{bmatrix}. \quad (12)$$

Let

$$s_i = [\mathbf{Ax}]_i = a_{i1}x_1 + \cdots + a_{in}x_n = \sum_j a_{ij}x_j. \quad (13)$$

Then,

$$\frac{\partial s_i}{\partial x_j} = a_{ij}. \quad (14)$$

So,

$$\frac{\partial(\mathbf{Ax})}{\partial \mathbf{x}^\top} = \begin{bmatrix} \frac{\partial s_1}{\partial x_1} & \cdots & \frac{\partial s_1}{\partial x_n} \\ \vdots & \ddots & \vdots \\ \frac{\partial s_n}{\partial x_1} & \cdots & \frac{\partial s_n}{\partial x_n} \end{bmatrix} = \mathbf{A}. \quad (15)$$

And,

$$\frac{\partial(\mathbf{A}\mathbf{x})^\top}{\partial \mathbf{x}} = \mathbf{A}^\top. \quad (16)$$

$$(5) \quad E = \|\mathbf{Ax}\|^2$$

$$E = \|\mathbf{Ax}\|^2 = (\mathbf{Ax})^\top (\mathbf{Ax}) = \sum_k \left[\sum_j a_{kj} x_j \right]^2. \quad (17)$$

$$\frac{\partial E}{\partial x_i} = 2 \sum_k \sum_j a_{ki} a_{kj} x_j = 2 \sum_j \left[\sum_k a_{ki} a_{kj} \right] x_j. \quad (18)$$

That is,

$$\frac{\partial E}{\partial x_i} = 2 \sum_j \left[\mathbf{A}^\top \mathbf{A} \right]_{ij} x_j. \quad (19)$$

Thus,

$$\frac{\partial E}{\partial \mathbf{x}} = 2 \mathbf{A}^\top \mathbf{Ax}. \quad (20)$$

(6) $E = \|\mathbf{Ax}\|^2$

$$E = \sum_i s_i^2 \quad (21)$$

where

$$s_i = \sum_j a_{ij} x_j. \quad (22)$$

$$\frac{\partial E}{\partial a_{ij}} = 2s_i \frac{\partial s_i}{\partial a_{ij}} = 2s_i x_j. \quad (23)$$

Thus,

$$\frac{\partial E}{\partial \mathbf{A}} = 2 \begin{bmatrix} s_1 \\ \vdots \\ s_n \end{bmatrix} [x_1 \cdots x_n] = 2\mathbf{Ax}\mathbf{x}^\top. \quad (24)$$

$$(7) E = \|\mathbf{B}\mathbf{A}\mathbf{x}\|^2$$

Let $\mathbf{y} = \mathbf{A}\mathbf{x}$. Then,

$$E = \|\mathbf{B}\mathbf{y}\|^2. \quad (25)$$

$$\frac{\partial E}{\partial \mathbf{B}} = 2\mathbf{B}\mathbf{y}\mathbf{y}^\top = 2\mathbf{B}\mathbf{A}\mathbf{x}\mathbf{x}^\top\mathbf{A}^\top. \quad (26)$$

$$(8) \quad E = \|\mathbf{B}\mathbf{A}\mathbf{x}\|^2$$

Let $\mathbf{C} = \mathbf{B}\mathbf{A}$. Then,

$$E = \|\mathbf{Cx}\|^2. \quad (27)$$

$$\frac{\partial E}{\partial \mathbf{x}} = 2\mathbf{C}^\top \mathbf{Cx} = 2\mathbf{A}^\top \mathbf{B}^\top \mathbf{B}\mathbf{Ax}. \quad (28)$$

$$(9) \quad E = \|\mathbf{B}\mathbf{A}\mathbf{x}\|^2$$

$$E = \|\mathbf{B}\mathbf{A}\mathbf{x}\|^2 = \sum_k \left[\sum_l \sum_m b_{kl} a_{lm} x_m \right]^2. \quad (29)$$

$$\begin{aligned} \frac{\partial E}{\partial a_{ij}} &= 2 \sum_k \left[\sum_l \sum_m b_{kl} a_{lm} x_m \right] b_{ki} x_j \\ &= 2 \sum_l \sum_m \left[\sum_k b_{ki} b_{kl} \right] a_{lm} x_m x_j \\ &= 2 \sum_l \sum_m \left[\mathbf{B}^\top \mathbf{B} \right]_{il} a_{lm} x_m x_j \\ &= 2 \left[\mathbf{B}^\top \mathbf{B} \mathbf{A} \mathbf{x} \right]_i x_j. \end{aligned} \quad (30)$$

So,

$$\frac{\partial E}{\partial \mathbf{A}} = 2 \mathbf{B}^\top \mathbf{B} \mathbf{A} \mathbf{x} \mathbf{x}^\top. \quad (31)$$