

矩阵相关知识汇总

1. tr , 矩阵的迹, 有关性质

$$\textcircled{1} \quad \text{tr}(\mathbf{A} \pm \mathbf{B}) = \text{tr}(\mathbf{A}) \pm \text{tr}(\mathbf{B})$$

$$\textcircled{2} \quad \text{如 } c \text{ 为常数, 则 } \text{tr}(c\mathbf{A}) = c\text{tr}(\mathbf{A})$$

$$\textcircled{3} \quad \text{tr}(c_1\mathbf{A} \pm c_2\mathbf{B}) = c_1\text{tr}(\mathbf{A}) \pm c_2\text{tr}(\mathbf{B})$$

$$\textcircled{4} \quad \text{tr}(\mathbf{A}^T) = \text{tr}(\mathbf{A}), \quad \text{tr}(\mathbf{A}^*) = [\text{tr}(\mathbf{A})]^* \quad (*\text{表示复数共轭}),$$

$$\text{tr}(\mathbf{A}^H) = [\text{tr}(\mathbf{A})]^* \quad (\text{H 表示共轭转置})$$

$$\textcircled{5} \quad \mathbf{A}_{m \times n}, \mathbf{B}_{n \times m} \text{ 则 } \text{tr}(\mathbf{AB}) = \text{tr}(\mathbf{BA})$$

$$\text{推广: } \text{tr}(\mathbf{ABC}) = \text{tr}(\mathbf{CAB}) = \text{tr}(\mathbf{BCA})$$

$$\textcircled{6} \quad \mathbf{A} \text{ 和 } \mathbf{B} \text{ 为 } m \times m \text{ 矩阵, 并且 } \mathbf{B} \text{ 非奇异, 则}$$

$$\text{tr}(\mathbf{BAB}^{-1}) = \text{tr}(\mathbf{B}^{-1}\mathbf{AB}) = \text{tr}(\mathbf{A})$$

$$\textcircled{7} \quad \text{若 } \mathbf{A} \text{ 为 } m \times n \text{ 矩阵, 则 } \text{tr}(\mathbf{A}^H\mathbf{A}) = 0 \Leftrightarrow \mathbf{A} = \mathbf{0} \quad (\text{零矩阵})$$

$$\textcircled{8} \quad \mathbf{x}^H\mathbf{Ax} = \text{tr}(\mathbf{Axx}^H) \text{ 和 } \mathbf{y}^H\mathbf{x} = \text{tr}(\mathbf{xy}^H)$$

$$\textcircled{9} \quad \text{tr} \begin{bmatrix} \mathbf{A} & \mathbf{B} \\ \mathbf{C} & \mathbf{D} \end{bmatrix} = \text{tr}(\mathbf{A}) + \text{tr}(\mathbf{D})$$

$$\textcircled{10} \quad \text{tr}(\mathbf{A}) = \lambda_1 + \lambda_2 + \cdots + \lambda_n$$

$$\textcircled{11} \quad \text{tr}(\mathbf{A}^k) = \sum_{i=1}^n \lambda_i^k$$

2. rank , 矩阵的秩, 性质

$$\textcircled{1} \quad \text{rank}(\mathbf{A}) = \text{rank}(\mathbf{A}^T)$$

$$\textcircled{2} \quad \text{若 } \mathbf{P}, \mathbf{Q} \text{ 非奇异, 则 } \text{rank}(\mathbf{PA}) = \text{rank}(\mathbf{AQ}) = \text{rank}(\mathbf{PAQ}) = \text{rank}(\mathbf{A})$$

$$\textcircled{3} \quad \text{rank} \begin{pmatrix} \mathbf{A} & \mathbf{0} \\ \mathbf{0} & \mathbf{B} \end{pmatrix} = \text{rank}(\mathbf{A}) + \text{rank}(\mathbf{B})$$

$$\textcircled{4} \quad \text{rank} \begin{pmatrix} \mathbf{A} & \mathbf{0} \\ \mathbf{C} & \mathbf{B} \end{pmatrix} \geq \text{rank}(\mathbf{A}) + \text{rank}(\mathbf{B})$$

$$\textcircled{5} \quad \mathbf{A} \text{ 为 } m \times n, \text{ 则 } \text{rank}(\mathbf{A}) \leq \min(m, n)$$

$$\textcircled{6} \quad \mathbf{A} \text{ 为 } m \times k, \mathbf{B} \text{ 为 } k \times n, \text{ 则}$$

$$\text{rank}(\mathbf{A}) + \text{rank}(\mathbf{B}) - k \leq \text{rank}(\mathbf{AB}) \leq \min \{ \text{rank}(\mathbf{A}), \text{rank}(\mathbf{B}) \}$$

$$\textcircled{7} \quad \mathbf{A}, \mathbf{B} \text{ 为 } m \times n, \text{ 则 } \text{rank}(\mathbf{A} + \mathbf{B}) \leq \text{rank}(\mathbf{A}) + \text{rank}(\mathbf{B})$$

$$\textcircled{8} \quad \text{rank}(\mathbf{AA}^T) = \text{rank}(\mathbf{A}^T \mathbf{A}) = \text{rank}(\mathbf{A})$$

$$\textcircled{9} \quad \text{设 } \mathbf{A} \text{ 为 } n \text{ 阶方阵, } \mathbf{A}^* \text{ 为 } \mathbf{A} \text{ 的伴随矩阵, 则}$$

$$\text{rank}(\mathbf{A}^*) = \begin{cases} n, & \text{rank}(\mathbf{A}) = n \\ 1, & \text{rank}(\mathbf{A}) = n - 1 \\ 0, & \text{rank}(\mathbf{A}) < n - 1 \end{cases}$$

3. 矩阵及向量范数

1) 向量范数

设 $\|\mathbf{x}\|$ 为以向量 \mathbf{x} 为自变量的非负实值函数, 且满足:

$$\textcircled{1} \text{ 非负性: 当 } \mathbf{x} \neq \mathbf{0}, \|\mathbf{x}\| > 0; \text{ 当 } \mathbf{x} = \mathbf{0}, \|\mathbf{x}\| = 0$$

$$\textcircled{2} \text{ 齐次性: 对 } \forall k \in \mathbf{P} (\mathbf{P} \text{ 为数域}), \|\mathbf{kx}\| = |k| \|\mathbf{x}\|$$

$$\textcircled{3} \text{ 三角不等式: } \forall \mathbf{x}, \mathbf{y} \in \mathbf{R}^n \text{ or } \mathbf{C}^n, \|\mathbf{x} + \mathbf{y}\| \leq \|\mathbf{x}\| + \|\mathbf{y}\|$$

则称 $\|\mathbf{x}\|$ 为向量 \mathbf{x} 的范数.

2) 常见的向量范数

$$\|\mathbf{x}\|_1 = \sum_{i=1}^n |x_i|$$

$$\|\mathbf{x}\|_2 = \left(\sum_{i=1}^n |x_i|^2 \right)^{1/2}, \quad \|\mathbf{x}\|_2^2 = \mathbf{x}^H \mathbf{x} (\text{复数域}), \mathbf{x}^T \mathbf{x} (\text{实数域})$$

$$\|\mathbf{x}\|_\infty = \max_{1 \leq i \leq n} |x_i|$$

$$\|\mathbf{x}\|_p = \left(\sum_{i=1}^n |x_i|^p \right)^{1/p}, \quad 1 \leq p < +\infty$$

3) 矩阵范数

定义和向量范数相似

4) 常见的矩阵范数

① Frobenius 范数: $\|A\|_F = \left(\sum_{i=1}^m \sum_{j=1}^n |a_{ij}|^2 \right)^{1/2} = \left[\text{tr}(A^H A) \right]^{1/2}$ (C域)

$$\|A\|_F = \left(\sum_{i=1}^m \sum_{j=1}^n a_{ij}^2 \right)^{1/2} = \left[\text{tr}(A^T A) \right]^{1/2} \text{ (R域)}$$

② $\|A\|_1 = \max_{1 \leq j \leq n} \sum_{i=1}^m |a_{ij}|$, 其中 A 为 $m \times n$, 列和

③ $\|A\|_\infty = \max_{1 \leq i \leq m} \sum_{j=1}^n |a_{ij}|$, 行和

④ $\|A\|_2 = \left[\lambda_{\max}(A^H A) \right]^{1/2}$

⑤ F 范数性质: $A \in \mathbf{R}^{m \times n}$, P 和 Q 分别为 m 阶和 n 阶正交矩阵

$$\|PAQ\|_F = \|A\|_F$$

⑥ 2 范数性质: $\|A\|_2 = \max_{\substack{\|x\|_2=1 \\ \|y\|_2=1}} |y^H A x|$

$$\|A^H\|_2 = \|A^T\|_2 = \|A\|_2$$

$$\|A^H A\|_2 = \|A\|_2^2$$

$$\|A\|_2^2 \leq \|A\|_1 \|A\|_\infty$$

设 A 为 $m \times n$, m 阶正交阵 P 和 n 阶正交阵 Q , $\|PAQ\|_2 = \|A\|_2$

△ 4. 导数或梯度

1) 对标量的导数

设 $m \times n$ 阶矩阵 $A(t)$ 的每一个元素均是标量 t 的函数, 则

$$\frac{d\mathbf{A}(t)}{dt} = \begin{bmatrix} \frac{da_{11}}{dt} & \frac{da_{12}}{dt} & \cdots & \frac{da_{1n}}{dt} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{da_{m1}}{dt} & \frac{da_{m2}}{dt} & \cdots & \frac{da_{mn}}{dt} \end{bmatrix}$$

设 $\mathbf{x}(t)$ 向量的每一个元素均是标量 t 的函数，则

$$\frac{d\mathbf{x}(t)}{dt} = \begin{bmatrix} \frac{dx_1}{dt} \\ \vdots \\ \frac{dx_n}{dt} \end{bmatrix}$$

2) 对向量变量的导数

(1) 数量函数对向量的导数

设 $f(\mathbf{x})$ 是以向量 $\mathbf{x} = \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix}$ 为自变量的数量函数，则

$$\frac{df(\mathbf{x})}{d\mathbf{x}} = \begin{bmatrix} \frac{\partial f}{\partial x_1} \\ \vdots \\ \frac{\partial f}{\partial x_n} \end{bmatrix} = \nabla_{\mathbf{x}} f$$

(2) 向量函数对向量的导数(梯度)

m 维行向量函数 $\mathbf{f}^T(\mathbf{x}) = [f_1(\mathbf{x}), f_2(\mathbf{x}), \dots, f_m(\mathbf{x})]$ ，对于 n 维列

量 \mathbf{x} 的梯度为一 $n \times m$ 矩阵，定义为：

$$\frac{\partial \mathbf{f}^T(\mathbf{x})}{\partial \mathbf{x}} = \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \frac{\partial f_2}{\partial x_1} & \cdots & \frac{\partial f_m}{\partial x_1} \\ \frac{\partial f_1}{\partial x_2} & \frac{\partial f_2}{\partial x_2} & \cdots & \frac{\partial f_m}{\partial x_2} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial f_1}{\partial x_n} & \frac{\partial f_2}{\partial x_n} & \cdots & \frac{\partial f_m}{\partial x_n} \end{bmatrix} = \nabla_{\mathbf{x}} \mathbf{f}$$

相似地， m 维列向量函数 $\mathbf{f}(\mathbf{x}) = \mathbf{y} = \begin{bmatrix} y_1 \\ \vdots \\ y_m \end{bmatrix}$ 对 n 维行向量 \mathbf{x}^T 的

梯度为：

$$\frac{\partial \mathbf{y}}{\partial \mathbf{x}^T} = \begin{bmatrix} \frac{\partial y_1}{\partial x_1} & \frac{\partial y_1}{\partial x_2} & \cdots & \frac{\partial y_1}{\partial x_n} \\ \frac{\partial y_2}{\partial x_1} & \frac{\partial y_2}{\partial x_2} & \cdots & \frac{\partial y_2}{\partial x_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial y_m}{\partial x_1} & \frac{\partial y_m}{\partial x_2} & \cdots & \frac{\partial y_m}{\partial x_n} \end{bmatrix}_{m \times n} = \nabla_{\mathbf{x}^T} \mathbf{y}$$

总之一句话：行对列，列对行，行不能对行，列不能对列。

(3) 矩阵函数对向量的导数

设矩阵函数 $\mathbf{A}(\mathbf{x})$ ，即 \mathbf{A} 的每一个元素 a_{ij} 均为向量 \mathbf{x} 的函数，

即

$$\mathbf{A}(\mathbf{x}) = \begin{bmatrix} a_{11}(\mathbf{x}) & a_{12}(\mathbf{x}) & \cdots & a_{1p}(\mathbf{x}) \\ a_{21}(\mathbf{x}) & a_{22}(\mathbf{x}) & \cdots & a_{2p}(\mathbf{x}) \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1}(\mathbf{x}) & a_{m2}(\mathbf{x}) & \cdots & a_{mp}(\mathbf{x}) \end{bmatrix}_{m \times p}$$

其中 $\mathbf{x} = (x_1, x_2, \dots, x_n)^T$ 为列向量，则

$$\frac{d\mathbf{A}(\mathbf{x})}{d\mathbf{x}} = \begin{bmatrix} \frac{\partial \mathbf{A}(\mathbf{x})}{\partial x_1} \\ \frac{\partial \mathbf{A}(\mathbf{x})}{\partial x_2} \\ \vdots \\ \frac{\partial \mathbf{A}(\mathbf{x})}{\partial x_n} \end{bmatrix}_{m \times np}, \quad \frac{d\mathbf{A}(\mathbf{x})}{d\mathbf{x}^T} = \begin{bmatrix} \frac{\partial \mathbf{A}(\mathbf{x})}{\partial x_1} & \frac{\partial \mathbf{A}(\mathbf{x})}{\partial x_2} & \dots & \frac{\partial \mathbf{A}(\mathbf{x})}{\partial x_n} \end{bmatrix}_{m \times np}$$

3) 实值函数对矩阵的梯度

设 $f = f(\mathbf{A})$ 是以矩阵 $\mathbf{A} \in \mathbf{R}^{m \times n}$ 为自变量的实值函数，则

$$\frac{df(\mathbf{A})}{d\mathbf{A}} = \begin{bmatrix} \frac{df}{da_{11}} & \frac{df}{da_{12}} & \dots & \frac{df}{da_{1n}} \\ \frac{df}{da_{21}} & \frac{df}{da_{22}} & \dots & \frac{df}{da_{2n}} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{df}{da_{m1}} & \frac{df}{da_{m2}} & \dots & \frac{df}{da_{mn}} \end{bmatrix}$$

以上为定义，下面开始讲例子。

$$\left(\begin{array}{l} \triangle \frac{\partial \mathbf{x}}{\partial \mathbf{x}^T} = \mathbf{I} \quad \frac{\partial \mathbf{x}^T}{\partial \mathbf{x}} = \mathbf{I} \quad \text{其中 } \mathbf{x} \text{ 为向量} \\ \triangle \frac{\partial \text{tr}(\mathbf{A}^T)}{\partial \mathbf{A}} = \mathbf{I} \quad \frac{\partial \text{tr}(\mathbf{A})}{\partial \mathbf{A}^T} = \mathbf{I} \quad \text{其中 } \mathbf{A} \text{ 为矩阵} \end{array} \right)$$

例1. \mathbf{A} 和 \mathbf{y} 均与 \mathbf{x} 无关，则

$$\frac{\partial \mathbf{x}^T \mathbf{A} \mathbf{y}}{\partial \mathbf{x}} = \mathbf{A} \mathbf{y} \quad \frac{\partial \mathbf{y}^T \mathbf{A} \mathbf{x}}{\partial \mathbf{x}} = \mathbf{A}^T \mathbf{y}$$

(\mathbf{A} 为矩阵， \mathbf{x} 和 \mathbf{y} 均为向量，下同)

例2. 若 \mathbf{A} 与 \mathbf{x} 无关，则 $\frac{\partial \mathbf{x}^T \mathbf{A} \mathbf{x}}{\partial \mathbf{x}} = \mathbf{A} \mathbf{x} + \mathbf{A}^T \mathbf{x}$

例3. $\frac{\partial \mathbf{x}^T \mathbf{A} \mathbf{y}}{\partial \mathbf{A}} = \mathbf{x} \mathbf{y}^T$

例4. $\frac{\partial \text{tr}(\mathbf{W})}{\partial \mathbf{W}} = \frac{\partial \text{tr}(\mathbf{W}^T)}{\partial \mathbf{W}} \triangleq \mathbf{I}$

$$\frac{\partial \text{tr}(\mathbf{W}^{-1})}{\partial \mathbf{W}} = -(\mathbf{W}^{-2})^T$$

$$\frac{\partial \text{tr}(\mathbf{x}\mathbf{y}^T)}{\partial \mathbf{x}} = \mathbf{y} = \frac{\partial \text{tr}(\mathbf{y}\mathbf{x}^T)}{\partial \mathbf{x}}$$

$$\frac{\partial \text{tr}(\mathbf{W}\mathbf{A})}{\partial \mathbf{W}} = \mathbf{A}^T = \frac{\partial \text{tr}(\mathbf{A}\mathbf{W})}{\partial \mathbf{W}}$$

$$\frac{\partial \text{tr}(\mathbf{W}\mathbf{W}^T)}{\partial \mathbf{W}} = 2\mathbf{W}$$

若 \mathbf{A} 与 \mathbf{W} 无关, 则 $\frac{\partial \text{tr}(\mathbf{W}^T \mathbf{A} \mathbf{W})}{\partial \mathbf{W}} = (\mathbf{A} + \mathbf{A}^T) \mathbf{W}$

$$\triangleq \frac{\partial \text{tr}(\mathbf{A} \mathbf{W}^{-1})}{\partial \mathbf{W}} = -(\mathbf{W}^{-1} \mathbf{A} \mathbf{W}^{-1})^T$$

$$\frac{\partial \text{tr}(\mathbf{W} \mathbf{A} \mathbf{W}^T \mathbf{B})}{\partial \mathbf{W}} = \mathbf{B} \mathbf{W} \mathbf{A} + \mathbf{B}^T \mathbf{W} \mathbf{A}^T$$

例5. \mathbf{y} 和 \mathbf{z} 均为向量 \mathbf{x} 的向量函数, 即 $\mathbf{y}(\mathbf{x}) = [y_1(\mathbf{x}), \dots, y_n(\mathbf{x})]^T$,

$\mathbf{z}(\mathbf{x}) = [z_1(\mathbf{x}), \dots, z_n(\mathbf{x})]$, 则有:

$$\frac{d(\mathbf{y}^T \mathbf{z})}{d\mathbf{x}} = \frac{d\mathbf{y}^T}{d\mathbf{x}} \mathbf{z} + \frac{d\mathbf{z}^T}{d\mathbf{x}} \mathbf{y}$$

$$\frac{d(\mathbf{y}^T \mathbf{z})}{d\mathbf{x}^T} = \mathbf{y}^T \frac{d\mathbf{z}}{d\mathbf{x}^T} + \mathbf{z}^T \frac{d\mathbf{y}}{d\mathbf{x}^T}$$

4. 复合函数微分法

① 设 $f = f(\mathbf{y})$ 是列向量 \mathbf{y} 的标量函数, 而 $\mathbf{y} = \mathbf{y}(t) = [y_1(t), \dots, y_n(t)]^T$,

则 f 对标量 t 的导数为:

$$\frac{df}{dt} = \frac{df}{d\mathbf{y}^T} \frac{d\mathbf{y}}{dt} = \frac{d\mathbf{y}^T}{dt} \frac{df}{d\mathbf{y}}$$

$$\textcircled{2} \text{ 设 } \mathbf{g} = \begin{bmatrix} g_1(\mathbf{y}) \\ g_2(\mathbf{y}) \\ \vdots \\ g_m(\mathbf{y}) \end{bmatrix}, \quad \mathbf{y} = \begin{bmatrix} y_1(\mathbf{x}) \\ y_2(\mathbf{x}) \\ \vdots \\ y_s(\mathbf{x}) \end{bmatrix}, \quad \mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}, \quad \mathbf{g}, \mathbf{y}, \mathbf{x} \text{ 均为向量, 则}$$

$$\left. \begin{aligned} \frac{d\mathbf{g}^T}{d\mathbf{x}}_{n \times m} &= \frac{d\mathbf{y}^T}{d\mathbf{x}} \frac{d\mathbf{g}^T}{d\mathbf{y}} \\ \frac{d\mathbf{g}}{d\mathbf{x}^T}_{m \times n} &= \frac{d\mathbf{g}}{d\mathbf{y}^T} \frac{d\mathbf{y}}{d\mathbf{x}^T} \end{aligned} \right\} \text{链式法则. 记忆要点: 能乘维数对就对}$$

5. 矩阵微分

设向量函数 $\mathbf{f}(\mathbf{c})$ 在 \mathbf{c} 可微分, 并且向量函数 $\mathbf{g}(\mathbf{b})$ 在 $\mathbf{b} = \mathbf{f}(\mathbf{c})$ 可微分,

则复合向量函数 $\mathbf{h}(\mathbf{x}) = \mathbf{g}(\mathbf{f}(\mathbf{x}))$ 在 \mathbf{c} 可微分, 且

$$D\mathbf{h}(\mathbf{c}) = (D[\mathbf{g}(\mathbf{b})])(D[\mathbf{f}(\mathbf{c})])$$

例子:

$$d(\text{tr} \mathbf{U}) = \text{tr}(d\mathbf{U}) \quad \Delta$$

$$d(\mathbf{UV}) = d(\mathbf{U})\mathbf{V} + \mathbf{U}d\mathbf{V} \quad \Delta$$

$$d(\mathbf{U}^T) = (d\mathbf{U})^T$$

$$d(\mathbf{AXB}) = A(d\mathbf{X})\mathbf{B}$$

$$d(\mathbf{XAX}^T) = (d\mathbf{X})\mathbf{AX}^T + \mathbf{XA}(d\mathbf{X})^T$$

$$d(\mathbf{X}^T \mathbf{AX}) = (d\mathbf{X})^T \mathbf{AX} + \mathbf{X}^T A d\mathbf{X}$$

$$d|\mathbf{X}| = |\mathbf{X}| \text{tr}(\mathbf{X}^{-1} d\mathbf{X})$$

$$d(\text{tr}(\mathbf{X}^T \mathbf{X})) = 2\text{tr}(\mathbf{X}^T d\mathbf{X}) \quad \Delta$$

$$d(\mathbf{X}^{-1}) = -\mathbf{X}^{-1}(d\mathbf{X})\mathbf{X}^{-1}$$

$$d \log(\mathbf{X}) = \mathbf{X}^{-1} d\mathbf{X}$$

$$d \log(\mathbf{X}^T \mathbf{AX}) = (\mathbf{X}^T \mathbf{AX})^{-1} \left[(d\mathbf{X})^T \mathbf{AX} + \mathbf{X}^T A d\mathbf{X} \right]$$

根据微分求标量函数的梯度:

两个重要公式:

$$df(\mathbf{x}) = A d\mathbf{x} \Leftrightarrow \nabla f(\mathbf{x}) = \frac{\partial f(\mathbf{x})}{\partial \mathbf{x}} = A^T$$

$$df(\mathbf{x}) = \text{tr}(A d\mathbf{x}) \Leftrightarrow \nabla f(\mathbf{x}) = \frac{\partial f(\mathbf{x})}{\partial \mathbf{x}} = A^T$$

例1. $\frac{\partial \text{tr}(\mathbf{X}^T A \mathbf{X})}{\partial \mathbf{X}} = ?$

$$\begin{aligned} d\text{tr}(\mathbf{X}^T A \mathbf{X}) &= \text{tr}[d(\mathbf{X}^T A \mathbf{X})] \\ &= \text{tr}[(d\mathbf{X})^T A \mathbf{X} + \mathbf{X}^T A d\mathbf{X}] \\ &= \text{tr}[\mathbf{X}^T A^T d\mathbf{X}] + \text{tr}[\mathbf{X}^T A d\mathbf{X}] \\ &= \text{tr}[(\mathbf{X}^T A^T + \mathbf{X}^T A) d\mathbf{X}] \end{aligned}$$

因此: $\frac{\partial \text{tr}(\mathbf{X}^T A \mathbf{X})}{\partial \mathbf{X}} = (A^T + A) \mathbf{X}$

例2. $\frac{\partial |\mathbf{X}|^2}{\partial \mathbf{X}} = ?$

$$d(|\mathbf{X}|^2) = 2|\mathbf{X}| d(|\mathbf{X}|) = 2|\mathbf{X}|^2 \text{tr}(\mathbf{X}^{-1} d\mathbf{X})$$

因此: $\frac{\partial |\mathbf{X}|^2}{\partial \mathbf{X}} = 2|\mathbf{X}|^2 \mathbf{X}^{-T}$

例3. $\frac{\partial \text{tr}(A \mathbf{X}^{-1})}{\partial \mathbf{X}} = ?$

$$\begin{aligned} d\text{tr}(A \mathbf{X}^{-1}) &= \text{tr}[d(A \mathbf{X}^{-1})] \\ &= \text{tr}[A d\mathbf{X}^{-1}] \\ &= -\text{tr}[A \mathbf{X}^{-1} (d\mathbf{X}) \mathbf{X}^{-1}] \\ &= -\text{tr}[\mathbf{X}^{-1} A \mathbf{X}^{-1} d\mathbf{X}] \end{aligned}$$

因此: $\frac{\partial \text{tr}(A \mathbf{X}^{-1})}{\partial \mathbf{X}} = -\mathbf{X}^{-T} A^T \mathbf{X}^{-T}$

例4. $\frac{\partial |\mathbf{X} \mathbf{X}^T|}{\partial \mathbf{X}} = ?$

$$\begin{aligned}
d|\mathbf{X}\mathbf{X}^T| &= |\mathbf{X}\mathbf{X}^T| \operatorname{tr}[(\mathbf{X}\mathbf{X}^T)^{-1} d(\mathbf{X}\mathbf{X}^T)] \\
&= |\mathbf{X}\mathbf{X}^T| \operatorname{tr}[(\mathbf{X}\mathbf{X}^T)^{-1} [(d\mathbf{X})\mathbf{X}^T + \mathbf{X}(d\mathbf{X})^T]] \\
&= |\mathbf{X}\mathbf{X}^T| \operatorname{tr}[(\mathbf{X}\mathbf{X}^T)^{-1} (d\mathbf{X})\mathbf{X}^T + (\mathbf{X}\mathbf{X}^T)^{-1} \mathbf{X}d(\mathbf{X})^T] \\
&= |\mathbf{X}\mathbf{X}^T| \operatorname{tr}[\mathbf{X}^T(\mathbf{X}\mathbf{X}^T)^{-1} d\mathbf{X} + (d\mathbf{X})\mathbf{X}^T(\mathbf{X}\mathbf{X}^T)^{-T}] \\
&= |\mathbf{X}\mathbf{X}^T| \operatorname{tr}[\mathbf{X}^T(\mathbf{X}\mathbf{X}^T)^{-1} d\mathbf{X} + \mathbf{X}^T(\mathbf{X}\mathbf{X}^T)^{-1} d\mathbf{X}] \\
&= 2|\mathbf{X}\mathbf{X}^T| \operatorname{tr}[\mathbf{X}^T(\mathbf{X}\mathbf{X}^T)^{-1} d\mathbf{X}]
\end{aligned}$$

因此： $\frac{\partial |\mathbf{X}\mathbf{X}^T|}{\partial \mathbf{X}} = 2|\mathbf{X}\mathbf{X}^T|(\mathbf{X}\mathbf{X}^T)^{-1} \mathbf{X}$