

矩阵求导法则 $\left\{ \begin{array}{l} \text{简洁} \\ \text{加速计算机计算速度} \end{array} \right.$

$$f: \mathbb{R} \rightarrow \mathbb{R}^{2 \times 2} \quad f(x) = \begin{bmatrix} x & x^2 \\ x^3 & x^4 \end{bmatrix}$$

$$f: \mathbb{R}^2 \rightarrow \mathbb{R}^{2 \times 2} \quad f(x_1, x_2) = \begin{bmatrix} x_1 + x_2 & x_1^2 + x_2^2 \\ x_1^3 + x_2^3 & x_1^4 + x_2^4 \end{bmatrix}$$

输入为向量函数 \rightarrow 输出为向量函数

矩阵求导:

$\frac{dA}{dB}$: 矩阵A中的每个元素对矩阵B中每一个元素求导

举例说明: $A \Rightarrow p \times 1$ $A \Rightarrow 1 \times p$ $A \Rightarrow p \times p$
 $B \Rightarrow 1 \times 1$ $B \Rightarrow 1 \times n$ $B \Rightarrow m \times n$
 则 $\frac{dA}{dB} \Rightarrow p \times 1$ 则 $\frac{dA}{dB} \Rightarrow p \times n$ 则 $\frac{dA}{dB} \Rightarrow p \times p \times m \times n$

求导秘诀: $\left\{ \begin{array}{l} \text{① 标量不变, 向量拉伸} \\ \text{② 前面横向拉, 后面纵向拉} \end{array} \right.$
 $p \times$ 拉伸

例1: $\frac{df(x)}{dx}$ 若 $f(x)$ 是标量函数 x 是向量

$$\text{即 } f(x) = f(x_1, x_2, \dots, x_n)$$

$$\text{则 } \frac{df(x)}{dx} = \begin{bmatrix} \frac{\partial f}{\partial x_1} \\ \frac{\partial f}{\partial x_2} \\ \vdots \\ \frac{\partial f}{\partial x_n} \end{bmatrix}$$

例2: $\frac{df(x)}{dx}$ 若 $f(x)$ 是向量 x 是标量

$$\text{即 } f(x) = \begin{bmatrix} f_1(x) \\ f_2(x) \\ \vdots \\ f_n(x) \end{bmatrix}$$

$$\text{则 } \frac{df(x)}{dx} = \left[\frac{\partial f_1}{\partial x} \quad \frac{\partial f_2}{\partial x} \quad \dots \quad \frac{\partial f_n}{\partial x} \right]$$

例3: $\frac{df(x)}{dx}$ 若 $f(x)$ 是向量, x 是向量

$$f(x) = \begin{bmatrix} f_1(x) \\ f_2(x) \\ \vdots \\ f_m(x) \end{bmatrix} \quad x = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}$$

$$\text{则 } \frac{\partial f}{\partial x} = \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \frac{\partial f_1}{\partial x_2} & \dots & \frac{\partial f_1}{\partial x_n} \\ \frac{\partial f_2}{\partial x_1} & \frac{\partial f_2}{\partial x_2} & \dots & \frac{\partial f_2}{\partial x_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial f_m}{\partial x_1} & \frac{\partial f_m}{\partial x_2} & \dots & \frac{\partial f_m}{\partial x_n} \end{bmatrix} \quad \text{的转置}$$

常见矩阵求导公式:

① $f(x) = A^T x$ $A = n \times 1$ $x = n \times 1$
 则 $\frac{df(x)}{dx} = A$ 同理若 $f(x) = x^T A$ 则 $\frac{df(x)}{dx} = A$

② $f(x) = x^T A x$ $x = n \times 1$ $A = n \times n$
 则 $\frac{df(x)}{dx} = (A + A^T)x$

最小二乘为例

$$Y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} \quad X = \begin{bmatrix} x_1^T \\ x_2^T \\ \vdots \\ x_n^T \end{bmatrix} \quad b = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_p \end{bmatrix} \quad \begin{matrix} X: n \times p \\ b: p \times 1 \\ Y: n \times 1 \end{matrix}$$

$$J(b) = \sum_{k=1}^n (y_i - x_i^T b)^2$$

$$\text{向量化形式为 } J(b) = (Y - Xb)^T (Y - Xb)$$

$$\begin{aligned}
 &= (Y^T - b^T X^T)(Y - Xb) \\
 &= Y^T Y - Y^T X b - b^T X^T Y + b^T X^T X b \\
 &= Y^T Y - 2Y^T X b + b^T X^T X b
 \end{aligned}$$

$$\begin{aligned}
 \text{则 } \frac{\partial J(b)}{\partial b} &= -2X^T Y + (X^T X + X^T X)b \\
 &= -2X^T Y + 2X^T X b \\
 &= 2X^T (Xb - Y)
 \end{aligned}$$

向量对向量求导:
 a 是与 x 无关的函数

$$\frac{\partial a}{\partial x} = 0$$

$$f(x) = x$$

$$\frac{\partial f}{\partial x} = 1$$

$$\frac{\partial AX}{\partial X} = A^T$$

$$\frac{\partial X^T A}{\partial X} = A$$

a 是与 x 无关函数.

$$\frac{\partial au}{\partial x} = a \frac{\partial u}{\partial x}$$

$$a = a(x) \quad u = u(x)$$

$$\frac{\partial au}{\partial x} = a \frac{\partial u}{\partial x} + \frac{\partial a}{\partial x} u^T$$

A 是矩阵, 与 x 无关

$$\frac{\partial AX}{\partial x} = \frac{\partial u}{\partial x} A^T$$