

冷知识: 我没学过 multivariable calculus.

以下为急搜 from D2L 2.4.

### 2.4.2 Partial Derivatives

$$y = f(x_1, x_2, \dots, x_n)$$

$$\frac{\partial y}{\partial x_i} = \lim_{h \rightarrow 0} \frac{f(x_1, \dots, x_i + h, \dots, x_n) - f(x_1, \dots, x_i, \dots, x_n)}{h}$$

### 2.4.3. Gradient

$$\nabla_x f(x) = \begin{bmatrix} \frac{\partial f}{\partial x_1} \\ \frac{\partial f}{\partial x_2} \\ \vdots \\ \frac{\partial f}{\partial x_n} \end{bmatrix}$$

无歧义时记为  $\nabla f(x)$ .

### Partial Differentiation Rule

Let  $x \in \mathbb{R}^n$ .

$$\Rightarrow \forall A \in \mathbb{R}^{m \times n}, \nabla_x A x = A^T$$

$$\forall A \in \mathbb{R}^{n \times m}, \nabla_x x^T A = A$$

$$\forall A \in \mathbb{R}^{n \times n}, \nabla_x x^T A x = (A + A^T)x$$

$$\nabla_x \|x\|^2 = \nabla_x x^T x = 2x$$

### Chain Rule

$$y = f(u_1, u_2, \dots, u_m)$$

$$u_i, u_i = g_i(x_1, x_2, \dots, x_n)$$

$$\begin{aligned} \Rightarrow \frac{\partial y}{\partial x_i} &= \frac{\partial y}{\partial u_1} \frac{\partial u_1}{\partial x_i} + \frac{\partial y}{\partial u_2} \frac{\partial u_2}{\partial x_i} + \dots + \frac{\partial y}{\partial u_m} \frac{\partial u_m}{\partial x_i} \\ &= \sum_{j=1}^m \frac{\partial y}{\partial u_j} \frac{\partial u_j}{\partial x_i} \end{aligned}$$

## Probability

① Bayes

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \quad (= \frac{P(AB)}{P(B)})$$

② Marginalization:

$$P(B) = \sum_A P(A, B)$$

③ Expectation:

$$E[X] = \sum_x x P(X=x)$$

if  $x \sim p$  (distribution)

$$E_{x \sim p}[f(x)] = \sum_x f(x) P(x)$$

④ To measure the bias between  $X$  and its expectation:

$$\begin{aligned} \text{Var}[X] &= E[(X - E[X])^2] \\ &= E[X^2] - E[X]^2 \end{aligned}$$

To measure the bias between  $f(x)$  and its expectation when  $x$  is distributed by  $f(x)$ :

$$\text{Var}[f(x)] = E[(f(x) - E[f(x)])^2]$$