

5. Linear Algebra & Matrix Calculus.

① p -Norm of vector

p should be $[0, \infty)$

$$\|x\|_p = \left(\sum_i |x_i|^p \right)^{1/p}$$

E.g. $\|x\|_1 = \sum_i |x_i|$

$$\|x\|_2 = \sqrt{\sum_i x_i^2}$$

$$\|x\|_0 = \sum_i \mathbb{1}(x_i \neq 0)$$

$$\|x\|_\infty = \max\{|x_i|\}$$

② p -Norm of matrix

$$\|A\|_p = \sup_{x \neq 0} \frac{\|Ax\|_p}{\|x\|_p}$$

E.g. $\|A\|_1 = \max_j \sum_{i=1}^m |A_{ij}|$ maximum column sum

$$\|A\|_2 = \sigma_{\max}(A)$$

$$\|A\|_{\infty} = \max_i \sum_j |A_{ij}| = \|A^T\|_1$$

$$\|A\|_F = \sqrt{\sum_{i,j} (A_{ij})^2} = \sqrt{\sum \sigma_i^2} \quad \text{Frobenius Norm}$$

Proof:

$$\|A\|_2 = \max_{x \neq 0} \frac{\|Ax\|}{\|x\|} = \max_{x \neq 0} \left\| A \frac{x}{\|x\|} \right\| = \max_{\|u\|=1} \|Au\|$$

$$= \max_{\|u\|_2=1} \|U\Sigma V^T u\| = \max_{\|u\|_2=1} \|\Sigma \hat{u}\| = \max_{\|u\|_2=1} \|\Sigma u\| = \sigma_{\max}(A)$$

$$\begin{aligned} \|A\|_F &= \left(\sum_{i,j} (A_{ij})^2 \right)^{1/2} = \sqrt{\text{Tr}(AA^T)} = \sqrt{\text{Tr}(U\Sigma U^T U\Sigma V^T)} = \sqrt{\text{Tr}(\Sigma\Sigma)} \\ &= \sqrt{\sum \sigma_i^2} \end{aligned}$$

$$\|A\|_{\infty} = \max_{x \neq 0} \frac{\|Ax\|_{\infty}}{\|x\|_{\infty}} = \max_{x \neq 0} \left\| A \cdot \frac{x}{\|x\|_{\infty}} \right\|_{\infty}$$

$$\text{Let } x' = x / \|x\|_{\infty}$$

$$\max \|Ax'\|_{\infty} \Rightarrow x' = \mathbb{1} \quad \text{and the result} \Rightarrow \max \text{row.}$$

$$\|A\|_1 = \max \frac{\|Ax\|_1}{\|x\|_1} \Rightarrow x^* = [0, 0, \dots, 1, 0, \dots, 0]^T$$

So it's obvious $\|A\|_1 = \|A^T\|_{\infty}$

③ High-dimensional Derivative.

* Dimension principles.

1) denominator's dimension will be arranged first.

$$\text{E.g. } \frac{\partial A^{x \times y \times z}}{\partial B^{m \times n \times k}} = C^{\underbrace{m \times n \times k} \times \underbrace{x \times y \times z}}$$

1) Scalar by vector $z \in \mathbb{R}, v \in \mathbb{R}^m$

$$\frac{\partial z}{\partial v} = \begin{bmatrix} \frac{\partial z}{\partial v_1} \\ \vdots \\ \frac{\partial z}{\partial v_m} \end{bmatrix}_{m \times 1}$$

2) Vector by scalar $z \in \mathbb{R}, v \in \mathbb{R}^m$

$$\frac{\partial v}{\partial z} = \left[\frac{\partial v_1}{\partial z}, \frac{\partial v_2}{\partial z}, \dots, \frac{\partial v_m}{\partial z} \right]$$

3) Vector by Vector $x \in \mathbb{R}^m, y \in \mathbb{R}^n$

$$\frac{\partial y}{\partial x} = \left[\frac{\partial y_1}{\partial x}, \dots, \frac{\partial y_n}{\partial x} \right]$$

$$= \begin{bmatrix} \frac{\partial y_1}{\partial x_1} \\ \vdots \\ \frac{\partial y_1}{\partial x_m} \end{bmatrix} = \begin{bmatrix} \frac{\partial y_1}{\partial x_1} & \dots & \frac{\partial y_n}{\partial x_1} \\ \vdots & \ddots & \vdots \\ \frac{\partial y_1}{\partial x_m} & \dots & \frac{\partial y_n}{\partial x_m} \end{bmatrix}_{m \times n}$$

Corollary 1: $A \in \mathbb{R}^{k \times m}$, $V \in \mathbb{R}^{m \times 1}$, $x \in \mathbb{R}^{n \times 1}$

A is not a function of x

$$\left[\frac{\partial AV}{\partial x} \right]^{n \times k} = \frac{\partial V}{\partial x} \cdot A^T$$

Corollary 2: $U \in \mathbb{R}^{m \times 1}$, $V \in \mathbb{R}^{m \times 1}$, $x \in \mathbb{R}^{n \times 1}$

$$\left[\frac{\partial U^T V}{\partial x} \right] = \frac{\partial U}{\partial x} \cdot V + \frac{\partial V}{\partial x} \cdot U$$

Corollary 3: Chain Rule.

$$\frac{\partial}{\partial x} f(g(x)) = \frac{\partial g(x)}{\partial x} \cdot \frac{\partial f(g(x))}{\partial g(x)}$$

4) Scalar by Matrix $z \in \mathbb{R}$, $A \in \mathbb{R}^{k \times n}$

$$\frac{\partial z}{\partial A} = \left[\frac{\partial z}{\partial A_{ij}} \right]_{k \times n}$$

Corollary 4. $A \in \mathbb{R}^{m \times n}$, $U \in \mathbb{R}^{m \times 1}$, $V \in \mathbb{R}^{n \times 1}$,

U, V are not function of A

$$\frac{\partial U^T A V}{\partial A} = V U^T$$

5) Vector by Matrix $x \in \mathbb{R}^{k \times 1}$ $A \in \mathbb{R}^{m \times n}$

$$\left[\frac{\partial x}{\partial A} \right] = \left[\frac{\partial x_1}{\partial A}, \frac{\partial x_2}{\partial A}, \dots, \frac{\partial x_k}{\partial A} \right]_{m \times n \times k} \quad \left[\frac{\partial x_i}{\partial A} \right]_{m \times n \times 1}$$

$$= \begin{bmatrix} \frac{\partial x}{\partial A(1,:)} \\ \frac{\partial x}{\partial A(2,:)} \\ \vdots \\ \frac{\partial x}{\partial A(m,:)} \end{bmatrix}_{m \times n \times k} \quad \left[\frac{\partial x}{\partial A(1,:)} \right]_{1 \times n \times k}$$

④ Tensor Multiplication

1) $A \in \mathbb{R}^{m \times n}$ $x \in \mathbb{R}^{k \times 1}$ $y \in \mathbb{R}^{k \times 1}$

$$\left[\frac{\partial x}{\partial A} \cdot y \right]_{m \times n} = \left[\frac{\partial x_1}{\partial A}, \frac{\partial x_2}{\partial A}, \dots, \frac{\partial x_k}{\partial A} \right] \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_k \end{bmatrix}$$

$$= \sum_{i=1}^k \frac{\partial x_i}{\partial A} \cdot y_i$$

2) $A \in \mathbb{R}^{m \times n}$, $x \in \mathbb{R}^{k \times 1}$ $B \in \mathbb{R}^{k \times D}$

$$\left[\frac{\partial x}{\partial A} B \right] = \left[\frac{\partial x_1}{\partial A}, \dots, \frac{\partial x_k}{\partial A} \right] \cdot \begin{bmatrix} B(1,:) \\ B(2,:) \\ \vdots \\ B(k,:) \end{bmatrix} = \sum_{i=1}^k \frac{\partial x_i}{\partial A} \cdot B(i,:)$$

$$= \left[\frac{\partial x_1}{\partial A}, \dots, \frac{\partial x_k}{\partial A} \right] \cdot [B_1, \dots, B_D]$$

Note that $\frac{\partial x_i}{\partial A} B_i$ will construct i^{th} channel of final tensor.