

Vector norms: assume $x \in \mathbb{R}^n$

1. 1-norm: $\|x\|_1 \triangleq \sum_{i=1}^n |x_i|$

2. 2-norm: $\|x\|_2 \triangleq \sqrt{\sum_{i=1}^n x_i^2}$

• often denoted as $\| \cdot \|$

3. ∞ -norm: $\|x\|_\infty \triangleq \max_{1 \leq i \leq n} |x_i|$

4. p -norm: $\|x\|_p \triangleq \left(\sum_{i=1}^n |x_i|^p \right)^{\frac{1}{p}}$, for $1 \leq p < \infty$

In \mathbb{R}^n , a function $\phi: \mathbb{R}^n \rightarrow \mathbb{R}$ defines a norm if:

(1) $\phi(x) \geq 0, \forall x \in \mathbb{R}^n$
and $\phi(x) = 0 \iff x = \vec{0}$ } $\phi(x) > 0$, if $x \neq \vec{0}$

(2) $\phi(\alpha x) = |\alpha| \phi(x), \forall x \in \mathbb{R}^n, \forall \alpha \in \mathbb{R}$

(3) $\phi(x+y) \leq \phi(x) + \phi(y), \forall x \in \mathbb{R}^n, y \in \mathbb{R}^n$

Examples:

1. verify $\|x\|_1$ satisfies the three conditions above.

2. $\|x\|_p$ is not a norm if $0 < p < 1$

Take $p = \frac{1}{2}$ for instance.

$$(1) \|x\|_{\frac{1}{2}} \geq 0, \quad \forall x \in \mathbb{R}^n$$

$$\|x\|_{\frac{1}{2}} = 0 \iff x = \vec{0}$$

$$\left(\sum_{i=1}^n |x_i|^p \right)^{\frac{1}{p}} = 0 \iff \sum_{i=1}^n |x_i|^p = 0 \iff |x_i|^p = 0, \forall i$$

$$\iff |x_i| = 0 \iff x_i = 0 \quad \forall i.$$

$$(2) \| \alpha x \|_{\frac{1}{2}} = |\alpha| \cdot \|x\|_{\frac{1}{2}}$$

$$\| \alpha x \|_{\frac{1}{2}} = \left(\sum_{i=1}^n |\alpha x_i|^{\frac{1}{2}} \right)^2 = \left(\sum_{i=1}^n |\alpha|^{\frac{1}{2}} |x_i|^{\frac{1}{2}} \right)^2$$

$$= (|\alpha|^{\frac{1}{2}} \sum_{i=1}^n |x_i|^{\frac{1}{2}})^2 = |\alpha| \left(\sum_{i=1}^n |x_i|^{\frac{1}{2}} \right)^2$$

$$= |\alpha| \cdot \|x\|_{\frac{1}{2}}$$

$$(3) \text{ pick } x = \begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix}, \quad y = \begin{bmatrix} 0 \\ 1 \\ \vdots \\ 0 \end{bmatrix}, \quad x+y = \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 0 \end{bmatrix}$$

$$\|x\|_{\frac{1}{2}} = 1, \quad \|y\|_{\frac{1}{2}} = 1, \quad \|x+y\|_{\frac{1}{2}} = \left(\sum_{i=1}^n |x_i+y_i|^{\frac{1}{2}} \right)^2$$

$$= 2^2 = 4$$

$$\|x+y\|_{\frac{1}{2}} > \|x\|_{\frac{1}{2}} + \|y\|_{\frac{1}{2}}$$

Therefore, $\|\cdot\|_{\frac{1}{2}}$ does not define a norm.

Weighted vector norm: given a matrix $A \in \mathbb{R}^{n \times n}$, if

A is symmetric and positive definite, then

$$\phi(x) = \|x\|_A \triangleq \sqrt{x^T A x}, \quad \forall x \in \mathbb{R}^n$$

defines a norm.

Recall: A symmetric if $A^T = A$

A is positive definite if $x^T A x > 0, \forall x \neq \vec{0}$

A is positive semi-definite if $x^T A x \geq 0, \forall x$.

Matrix norm: assume $X \in \mathbb{R}^{m \times n}$, $m \leq n$

$$X = \begin{bmatrix} | & | & & | \\ \vec{x}_1 & \vec{x}_2 & \dots & \vec{x}_n \\ | & | & & | \end{bmatrix} = \begin{bmatrix} - & \vec{x}_1^T & - \\ - & \vec{x}_2^T & - \\ - & \vdots & - \\ - & \vec{x}_m^T & - \end{bmatrix}$$

1. matrix 1-norm:

$$\|X\|_1 \triangleq \max_{\|y\|_1=1} \|Xy\|_1 = \max_{1 \leq j \leq n} \|\vec{x}_j\|_1$$

2. matrix ∞ -norm:

$$\|X\|_\infty \triangleq \max_{\|y\|_\infty=1} \|Xy\|_\infty = \max_{1 \leq i \leq m} \|\tilde{x}_i\|_1$$

3. Matrix 2-norm:

$$\|X\|_2 \triangleq \max_{\|y\|_2=1} \|Xy\|_2 = \sqrt{\sigma_{\max}(X)}$$

maximum singular value of X

4. Frobenius norm:

$$\|X\|_F = \sqrt{\sum_{i=1}^m \sum_{j=1}^n |x_{ij}|^2}$$

5. Nuclear norm:

$$\|X\|_* \triangleq \sum_{i=1}^m \sigma_i(X)$$

$\sigma_i(X)$ is the i -th singular value of X

Example:

$$X = \begin{bmatrix} -1 & 2 & 0 \\ 3 & -3 & 1 \end{bmatrix}$$

Annotations: Row 1 has 3 elements, Row 2 has 3 elements. Column 1 has 2 elements, Column 2 has 2 elements, Column 3 has 2 elements.

① What is $\|X\|_1$? $\|X\|_1 = 5$

② What is $\|X\|_\infty$? $\|X\|_\infty = 7$

③ What is $\|X\|_F$? $\|X\|_F = \sqrt{(-1)^2 + 2^2 + 0^2 + 3^2 + (-3)^2 + 1^2} = \sqrt{24}$

④ What is $\|X\|_2$ and $\|X\|_x$?

Compute eigenvalues of

$$XX^T = \begin{bmatrix} -1 & 2 & 0 \\ 3 & -3 & 1 \end{bmatrix} \begin{bmatrix} -1 & 3 \\ 2 & -3 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 5 & -9 \\ -9 & 19 \end{bmatrix}$$

$$\det(\lambda I - XX^T) = \det \left(\begin{bmatrix} \lambda - 5 & 9 \\ 9 & \lambda - 19 \end{bmatrix} \right) = 0$$

Assume the roots are $\lambda_1 \geq \lambda_2 > 0$

$$\text{Then } \|X\|_2 = \sqrt{\lambda_1}, \quad \|X\|_x = \sqrt{\lambda_1} + \sqrt{\lambda_2}$$

Properties about matrix norm

$$① \quad \|Ax\|_1 \leq \|A\|_1 \cdot \|x\|_1, \quad \forall x \in \mathbb{R}^n, \quad \forall A \in \mathbb{R}^{m \times n}$$

$$\text{because } \|A\|_1 = \max_{\|y\|_1=1} \|Ay\|_1 = \max_{y \neq 0} \frac{\|Ay\|_1}{\|y\|_1} \geq \frac{\|Ax\|_1}{\|x\|_1}$$

$$\left\| \frac{y}{\|y\|_1} \right\|_1 = 1$$

$$② \quad \|Ax\|_\infty \leq \|A\|_\infty \cdot \|x\|_\infty$$

$$③ \quad \|Ax\| \leq \|A\|_2 \cdot \|x\|$$

$$④ \quad \|AB\|_F \leq \|A\|_2 \cdot \|B\|_F$$

Gradient : Let $f: \mathbb{R}^n \rightarrow \mathbb{R}$ be a differentiable function

Its gradient is defined:

$$\nabla f(x) = \begin{bmatrix} \frac{\partial f}{\partial x_1}(x) \\ \frac{\partial f}{\partial x_2}(x) \\ \vdots \\ \frac{\partial f}{\partial x_n}(x) \end{bmatrix} \in \mathbb{R}^n$$

Example: Let $f(x) = \frac{1}{2} x^T Q x + c^T x$, where $Q = Q^T \in \mathbb{R}^{n \times n}$

What is $\nabla f(x)$?

First, let

$$Q = \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix}, \quad c = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

$$\text{Then } f(x) = \frac{1}{2} [x_1, x_2] \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + [1, 1] \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

$$= \frac{1}{2} (2x_1^2 + 2x_1x_2 + 2x_2^2) + (x_1 + x_2)$$

$$\frac{\partial f}{\partial x_1}(x) = 2x_1 + x_2 + 1, \quad \frac{\partial f}{\partial x_2}(x) = x_1 + 2x_2 + 1$$

$$\text{So } \nabla f(x) = \begin{bmatrix} 2x_1 + x_2 + 1 \\ x_1 + 2x_2 + 1 \end{bmatrix} = Qx + c$$

Claim: for general $n \geq 1$, $Q = Q^T \in \mathbb{R}^{n \times n}$, $c \in \mathbb{R}^n$

$$\nabla f(x) = \nabla \left(\frac{1}{2} x^T Q x + c^T x \right) = Qx + c$$

Remark: for $f(x) = \frac{1}{2} x^T Q x + c^T x + d$, where $Q \in \mathbb{R}^{n \times n}$
but Q may not be symmetric,

$$\nabla f(x) = \frac{1}{2} (Q + Q^T) x + c$$

Pf: $f(x) = \frac{1}{2} x^T Q x + c^T x + d$

$$= \frac{1}{4} x^T Q x + \frac{1}{4} x^T Q x + c^T x + d$$

$$= \frac{1}{4} x^T Q x + \frac{1}{4} (x^T Q x)^T + c^T x + d$$

$$= \frac{1}{4} x^T Q x + \frac{1}{4} x^T Q^T x + c^T x + d$$

$$= \frac{1}{2} x^T \left(\frac{1}{2} (Q + Q^T) \right) x + c^T x + d$$

Example: Let $f(x) = \frac{1}{2} \|Ax - b\|^2$. What is $\nabla f(x)$?

Solution: $f(x) = \frac{1}{2} (Ax - b)^T (Ax - b)$

$$= \frac{1}{2} (x^T A^T - b^T) (Ax - b)$$

$$= \frac{1}{2} \left(x^T A^T A x - \underbrace{x^T A^T b}_{\langle A^T b, x \rangle} - \underbrace{b^T A x}_{\langle A^T b, x \rangle} + b^T b \right)$$

$$= \frac{1}{2} x^T A A^T x - (A^T b)^T x + \frac{1}{2} b^T b$$

$$\text{so } \nabla f(x) = A^T A x - A^T b = A^T (A x - b)$$

Hessian matrix: assume $f: \mathbb{R}^n \rightarrow \mathbb{R}$ is end-order differentiable

$$\nabla^2 f(x) = \begin{pmatrix} \frac{\partial^2 f}{\partial x_1^2} & \frac{\partial^2 f}{\partial x_2 \partial x_1} & \dots & \frac{\partial^2 f}{\partial x_n \partial x_1} \\ \vdots & & & \\ \frac{\partial^2 f}{\partial x_1 \partial x_i} & \frac{\partial^2 f}{\partial x_2 \partial x_i} & \dots & \frac{\partial^2 f}{\partial x_n \partial x_i} \\ \vdots & & & \\ \frac{\partial^2 f}{\partial x_1 \partial x_n} & \frac{\partial^2 f}{\partial x_2 \partial x_n} & \dots & \frac{\partial^2 f}{\partial x_n^2} \end{pmatrix} \in \mathbb{R}^{n \times n}$$

← i th row is $\left(\nabla \frac{\partial f}{\partial x_i}(x) \right)^T$

Example: Let $f(x) = \frac{1}{2} x^T Q x + c^T x + d$, where $Q = Q^T \in \mathbb{R}^{n \times n}$

what is $\nabla^2 f(x)$? ← $\nabla^2 f(x) = Q = \frac{1}{2}(Q + Q^T)$

First, let $Q = \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix}$, $c = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$

Then $\frac{\partial f}{\partial x_1}(x) = 2x_1 + x_2 + 1$, $\frac{\partial f}{\partial x_2}(x) = x_1 + 2x_2 + 1$

$$\nabla \frac{\partial f}{\partial x_1}(x) = \nabla (2x_1 + x_2 + 1) = \begin{bmatrix} 2 \\ 1 \end{bmatrix}, \quad \nabla^2 f(x) = \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix} = Q$$

$$\nabla \frac{\partial f}{\partial x_2}(x) = \nabla (x_1 + 2x_2 + 1) = \begin{bmatrix} 1 \\ 2 \end{bmatrix}$$

Example: for $f(x) = \frac{1}{2} \|Ax - b\|^2$

$$\text{Recall } f(x) = \frac{1}{2} x^T A^T A x - (A^T b)^T x + \frac{1}{2} b^T b$$

$$\text{So } \nabla^2 f(x) = A^T A$$

Example: Let $f(x) = \log(1 - \exp(a^T x + b))$, $\forall x \in \mathbb{R}^n$

$$\text{Take } a = \begin{bmatrix} 1 \\ 2 \end{bmatrix}, \quad b = -1$$

$$f(x) = \log(1 - \exp(x_1 + 2x_2 - 1))$$

$$\frac{\partial f}{\partial x_1}(x) = \frac{1}{1 - \exp(x_1 + 2x_2 - 1)} \cdot \frac{\partial(1 - \exp(x_1 + 2x_2 - 1))}{\partial x_1}$$

$$= \frac{1}{1 - \exp(x_1 + 2x_2 - 1)} \left(-\exp(x_1 + 2x_2 - 1) \right) \cdot \frac{\partial(x_1 + 2x_2 - 1)}{\partial x_1}$$

$$= \frac{1}{1 - \exp(x_1 + 2x_2 - 1)} \left(-\exp(x_1 + 2x_2 - 1) \right)$$

$$= \frac{-1}{\exp(-x_1 - 2x_2 + 1) - 1} = \frac{1}{1 - \exp(-x_1 - 2x_2 + 1)}$$

$$\frac{\partial f}{\partial x_2}(x) = \frac{1}{1 - \exp(x_1 + 2x_2 - 1)} \cdot \frac{2(1 - \exp(x_1 + 2x_2 - 1))}{2x_2}$$

$$= \frac{1}{1 - \exp(x_1 + 2x_2 - 1)} (-\exp(x_1 + 2x_2 - 1)) \cdot \frac{2(x_1 + 2x_2 - 1)}{2x_2}$$

$$= \frac{1}{1 - \exp(x_1 + 2x_2 - 1)} (-\exp(x_1 + 2x_2 - 1)) \cdot 2$$

$$= \frac{-2}{\exp(-x_1 - 2x_2 + 1) - 1} = \frac{2}{1 - \exp(-x_1 - 2x_2 + 1)}$$

$$\text{So } \nabla f(x) = \begin{bmatrix} \frac{1}{1 - \exp(-x_1 - 2x_2 + 1)} \\ \frac{2}{1 - \exp(-x_1 - 2x_2 + 1)} \end{bmatrix} = \frac{1}{1 - \exp(-x_1 - 2x_2 + 1)} \begin{bmatrix} 1 \\ 2 \end{bmatrix}$$

$$= \frac{1}{1 - \exp(-a^T x - b)} a$$

$$\frac{\partial}{\partial x_1} \left(\frac{\partial f}{\partial x_1} \right)$$

$$= - \frac{1}{(1 - \exp(-x_1 - 2x_2 + 1))^2} \cdot \frac{2(1 - \exp(-x_1 - 2x_2 + 1))}{2x_1}$$

$$= - \frac{1}{(1 - \exp(-x_1 - 2x_2 + 1))^2} \left(-\exp(-x_1 - 2x_2 + 1) \right) \cdot \frac{\partial(-x_1 - 2x_2 + 1)}{\partial x_1}$$

$$= - \frac{1}{(1 - \exp(-x_1 - 2x_2 + 1))^2} \left(-\exp(-x_1 - 2x_2 + 1) \right) \cdot (-1)$$

$$= - \frac{\exp(-x_1 - 2x_2 + 1)}{(1 - \exp(-x_1 - 2x_2 + 1))^2}$$

$$\frac{\partial}{\partial x_2} \left(\frac{\partial f}{\partial x_1} \right)$$

$$= - \frac{1}{(1 - \exp(-x_1 - 2x_2 + 1))^2} \cdot \frac{\partial(1 - \exp(-x_1 - 2x_2 + 1))}{\partial x_2}$$

$$= - \frac{1}{(1 - \exp(-x_1 - 2x_2 + 1))^2} \left(-\exp(-x_1 - 2x_2 + 1) \right) \cdot \frac{\partial(-x_1 - 2x_2 + 1)}{\partial x_2}$$

$$= - \frac{1}{(1 - \exp(-x_1 - 2x_2 + 1))^2} \left(-\exp(-x_1 - 2x_2 + 1) \right) \cdot (-2)$$

$$2 \cdot \exp(-x_1 - 2x_2 + 1)$$

$$= - \frac{1}{(1 - \exp(-x_1 - 2x_2 + 1))^2}$$

$$\text{So } \nabla \left(\frac{\partial f}{\partial x_1} \right) = - \frac{\exp(-x_1 - 2x_2 + 1)}{(1 - \exp(-x_1 - 2x_2 + 1))^2} \begin{bmatrix} 1 \\ 2 \end{bmatrix}$$

Check after class!

$$\nabla \left(\frac{\partial f}{\partial x_2} \right) = - \frac{\exp(-x_1 - 2x_2 + 1)}{(1 - \exp(-x_1 - 2x_2 + 1))^2} \begin{bmatrix} 2 \\ 4 \end{bmatrix}$$

$$\nabla f(x) = - \frac{\exp(-x_1 - 2x_2 + 1)}{(1 - \exp(-x_1 - 2x_2 + 1))^2} \begin{bmatrix} 1 & 2 \\ 2 & 4 \end{bmatrix}$$

$$= - \frac{\exp(-a^T x - b)}{(1 - \exp(-a^T x - b))^2} a a^T$$