Norms on $\mathbb{R}^{n \times n}$ (matrix norms)

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Induced Matrix Norms

Given a norm $\|\cdot\|$ on \mathbb{R}^n , the corresponding induced (or subordinate) matrix norm

$$||A|| := \max_{v \in \mathbb{R}^{n}, v \neq 0} \frac{||Av||}{||v||} = \max_{w \in \mathbb{R}^{n}, ||w||=1} ||Aw||$$

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Matrix *p*-norm

$$\|A\|_{p} := \max_{w \in \mathbb{R}^n, \, \|w\|_{p}=1} \, \|Aw\|_{p},$$

where $||w||_{p} = \sqrt[p]{|w_{1}|^{p} + |w_{2}|^{p} + \dots + |w_{n}|^{p}}$

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Characterizations of the 1-norm, ∞ -norm

1-norm is the maximal column sum

$$\|A\|_{1} := \max_{w \in \mathbb{R}^{n}, \|w\|_{1}=1} \|Aw\|_{1} = \max_{k=1,...,n} \sum_{j=1}^{n} |a_{jk}| = \max_{k=1,...,n} \|a_{k}\|_{1}$$

 ∞ -norm is the maximal row sum

$$\|A\|_{\infty} := \max_{w \in \mathbb{R}^n, \|w\|_{\infty} = 1} \|Aw\|_{\infty} = \max_{j=1,...,n} \sum_{k=1}^n |a_{jk}|$$

Theorem

For every $A \in \mathbb{R}^{n \times n}$, we have

$$\|A\|_2 = \sqrt{\lambda_n}$$

where λ_n denotes the largest eigenvalue of $A^T A$.



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Example.

$$A = \begin{bmatrix} 2 & 5 \\ -6 & 1 \end{bmatrix}, \quad A^{\mathsf{T}}A = \begin{bmatrix} 2 & -6 \\ 5 & 1 \end{bmatrix} \begin{bmatrix} 2 & 5 \\ -6 & 1 \end{bmatrix} = \begin{bmatrix} 40 & 4 \\ 4 & 26 \end{bmatrix}$$

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Characteristic polynomial of $A^T A$

$$p(\lambda) = \det(A^T A - \lambda I) = (40 - \lambda)(26 - \lambda) - 16 = \lambda^2 - 66\lambda + 1024$$

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Eigenvalues of $A^T A$: $33 \pm \sqrt{65}$, $||A||_2 = \sqrt{33 + \sqrt{65}}$

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$$A^{T}Aq = \lambda q \implies \lambda = rac{q^{T}A^{T}Aq}{q^{T}q} = rac{\|Aq\|_{2}^{2}}{\|q\|_{2}^{2}} \ge 0$$

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Sort them from smallest to largest, i.e.,

$$\lambda_1 \leq \lambda_2 \leq \cdots \leq \lambda_n$$
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Denote with *q_j* the eigenvector corresponding to λ_j s.t. {*q*₁,..., *q_n*} is orthonormal.

Expand any $w \in \mathbb{R}^n$, $||w||_2 = 1$ in terms of $\{q_1, \ldots, q_n\}$, that is

$$\boldsymbol{w} = \alpha_1 \boldsymbol{q}_1 + \alpha_2 \boldsymbol{q}_2 + \dots + \alpha_n \boldsymbol{q}_n$$

for some $\alpha_1, \alpha_2, \ldots, \alpha_n \in \mathbb{R}$



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for some $\alpha_1, \alpha_2, \ldots, \alpha_n \in \mathbb{R}$ s.t.

$$\alpha_1^2 + \alpha_2^2 + \dots + \alpha_n^2 = 1 \tag{1}$$

► (1) follows from

$$1 = \boldsymbol{w}^{T} \boldsymbol{w} = (\alpha_{1} \boldsymbol{q}_{1} + \dots + \alpha_{n} \boldsymbol{q}_{n})^{T} (\alpha_{1} \boldsymbol{q}_{1} + \dots + \alpha_{n} \boldsymbol{q}_{n})$$
$$= \alpha_{1}^{2} + \dots + \alpha_{n}^{2}.$$

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Specifically, for $w = q_n$ we have

$$\|Aq_n\|_2 = \sqrt{q_n^T A^T A q_n} = \sqrt{q_n^T (\lambda_n q_n)} = \sqrt{\lambda_n}$$

hence the result.