

## Math Preliminaries

- Norms and unit balls
- Inequalities
- Linear Algebra

## Norm Definition

- Norm

$$\mathbb{F} = \mathbb{R} \text{ or } \mathbb{C}, \quad V = \mathbb{F}^n, \quad \|\cdot\| : V \rightarrow \mathbb{R}$$

1.  $\forall a \in \mathbb{F}, \mathbf{v} \in V : \quad \|a\mathbf{v}\| = |a| \|\mathbf{v}\|.$
2.  $\forall \mathbf{v}_1, \mathbf{v}_2 \in V : \quad \|\mathbf{v}_1 + \mathbf{v}_2\| \leq \|\mathbf{v}_1\| + \|\mathbf{v}_2\|.$
3.  $\forall \mathbf{v} \in V : \quad \|\mathbf{v}\| \geq 0.$
4.  $\|\mathbf{v}\| = 0 \iff \mathbf{v} = 0.$

- Example

$$V = \mathbb{R}, \quad \|\mathbf{v}\| \triangleq \sqrt{v_1^2 + v_2^2 + \cdots + v_n^2}$$



# Well-known Norms

- $\ell_p$  norms

$$\|\mathbf{v}\|_{\ell_p} \text{ or } \|\mathbf{v}\|_p \triangleq \sqrt[p]{|v_1|^p + |v_2|^p + \cdots + |v_n|^p}$$

$$\|\mathbf{v}\|_{\ell_\infty} \text{ or } \|\mathbf{v}\|_\infty \triangleq \lim_{p \rightarrow \infty} \|\mathbf{v}\|_p = \max_{1 \leq i \leq n} |v_i|$$

$$\|\mathbf{v}\|_{\ell_0} \text{ or } \|\mathbf{v}\|_0 \triangleq |\{i, v_i \neq 0\}|$$

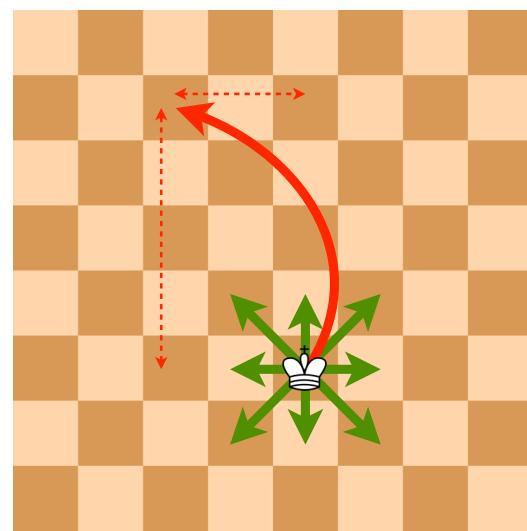
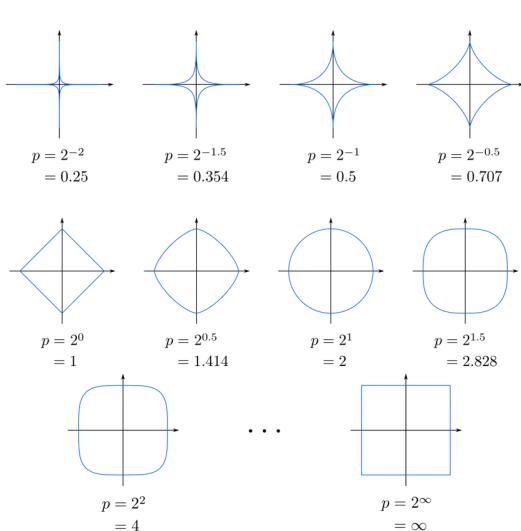
- $\ell_p$  is a norm for  $p \geq 1$ .
- Triangle inequality is not generally satisfied for  $0 \leq p < 1$ .

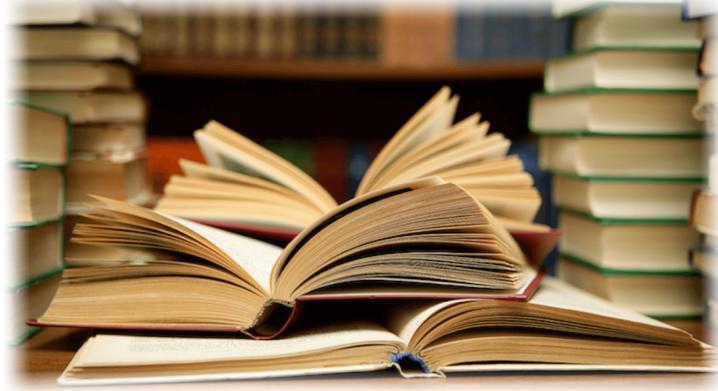


# Unit ball of Well-Known Norms

- Unit ball

$$B_1(\mathbb{F}^n; \ell_p) \triangleq \{\mathbf{x} \in \mathbb{F}^n \mid \|\mathbf{x}\|_p = 1\}$$





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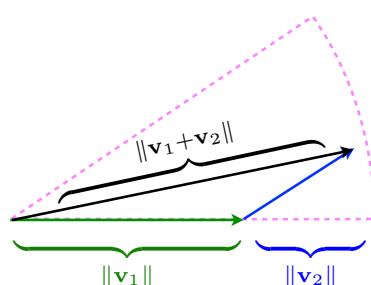
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## Inequalities related to Norms

- Triangle inequality

$$\|\mathbf{v}_1 + \mathbf{v}_2\| \leq \|\mathbf{v}_1\| + \|\mathbf{v}_2\|$$

$$\Rightarrow \|\mathbf{v}_1 - \mathbf{v}_2\| \leq \|\mathbf{v}_1\| + \|\mathbf{v}_2\| , \quad \|\mathbf{v}_1\| - \|\mathbf{v}_2\| \leq \|\mathbf{v}_1 \pm \mathbf{v}_2\|$$

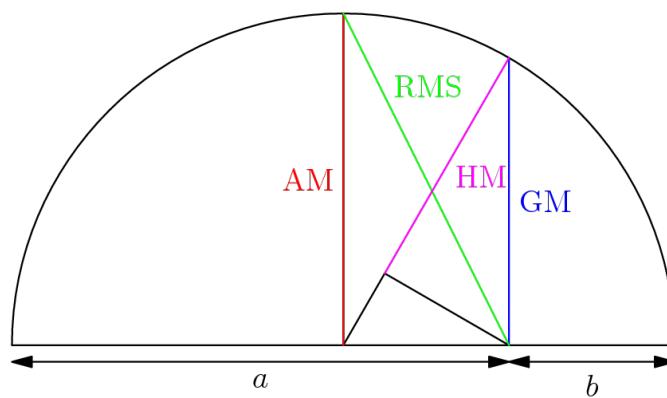




# Inequalities related to Norms

- HM-GM-AM-RMS inequality

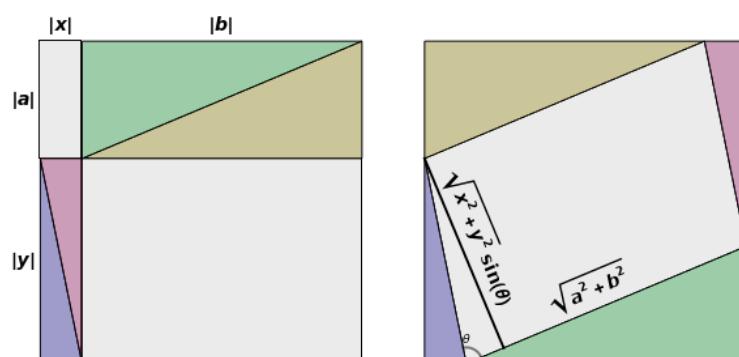
$$\underbrace{\frac{n}{\frac{1}{|x_1|} + \dots + \frac{1}{|x_n|}}}_{\text{HM}} \leq \underbrace{\sqrt[n]{|x_1 \dots x_n|}}_{\text{GM}} \leq \underbrace{\frac{|x_1| + \dots + |x_n|}{n}}_{\text{AM}} \leq \underbrace{\sqrt{\frac{|x_1|^2 + \dots + |x_n|^2}{n}}}_{\text{RMS}}$$



# Inequalities related to Norms

- Cauchy-Schwarz inequality

$$(|x_1y_1| + \dots + |x_ny_n|)^2 \leq (|x_1|^2 + \dots + |x_n|^2)(|y_1|^2 + \dots + |y_n|^2)$$





# Inequalities related to Norms

- Young's inequality

$$\frac{1}{p} + \frac{1}{q} = 1 \Rightarrow |xy| \leq \frac{|x|^p}{p} + \frac{|y|^q}{q}$$

$$\log(\cdot) = \text{concave} \Rightarrow \forall \begin{cases} 0 < \alpha < 1 \\ 0 < w, z \end{cases} : \alpha \log(z) + (1 - \alpha) \log(w) \leq \log(\alpha z + (1 - \alpha)w)$$

$$\Rightarrow z^\alpha \cdot w^{(1-\alpha)} \leq \alpha z + (1 - \alpha)w$$

$$\alpha = \frac{1}{p}, z = |x|^p, w = |y|^q \Rightarrow \checkmark$$



# Inequalities related to Norms

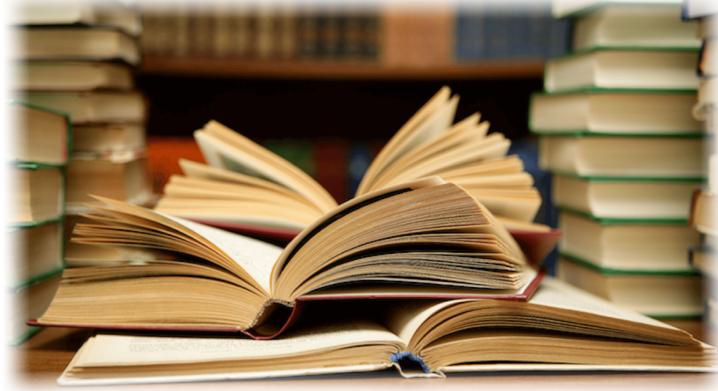
- Hölder's inequality

$$\frac{1}{p} + \frac{1}{q} = 1 \Rightarrow |x_1 y_1| + \cdots + |x_n y_n| \leq \sqrt[p]{|x_1|^p + \cdots + |x_n|^p} \cdot \sqrt[q]{|y_1|^q + \cdots + |y_n|^q}$$

$$\langle \mathbf{x}, \mathbf{y} \rangle \leq \|\mathbf{x}\|_{\ell_p} \cdot \|\mathbf{y}\|_{\ell_q}$$

$$\left| \frac{x_i}{\|\mathbf{x}\|_p} \cdot \frac{y_i}{\|\mathbf{y}\|_q} \right| \stackrel{\text{Young}}{\leq} \frac{1}{p} \frac{|x_i|^p}{\|\mathbf{x}\|_p^p} + \frac{1}{q} \frac{|y_i|^q}{\|\mathbf{y}\|_q^q}$$

$$\Rightarrow \frac{\sum_{i=1}^n |x_i y_i|}{\|\mathbf{x}\|_p \|\mathbf{y}\|_q} \leq \underbrace{\frac{1}{p} \frac{\sum_{i=1}^n |x_i|^p}{\|\mathbf{x}\|_p^p}}_{=1} + \underbrace{\frac{1}{q} \frac{\sum_{i=1}^n |y_i|^q}{\|\mathbf{y}\|_q^q}}_{=1} = 1 \Rightarrow \checkmark$$



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## Eigenvalues and Eigenvectors



- Linear operators

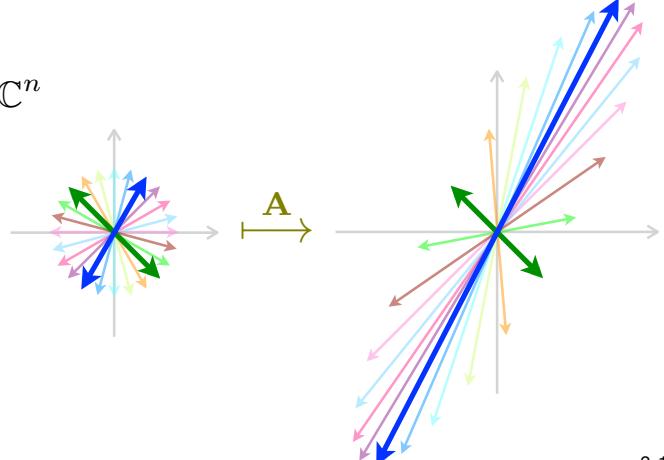
$$\mathbf{A} \in \mathbb{C}^{n \times n}$$

If  $\lambda \in \mathbb{C}$ ,  $\mathbf{v} \in \mathbb{C}^n$  &  $\mathbf{A} \cdot \mathbf{v} = \lambda \mathbf{v}$   $\Rightarrow$   $\begin{cases} \lambda & : \text{eignevalue} \\ \mathbf{v} & : \text{eignevector} \end{cases}$

- Linear systems theory

$$\mathbf{v} \in \mathbb{C}^n \xrightarrow{\quad \boxed{L} \quad} \mathbf{A}\mathbf{v} \in \mathbb{C}^n$$

$$\mathbf{A} = \begin{bmatrix} 2 & 1 \\ 2 & 3 \end{bmatrix} \Rightarrow$$





# Eigenvalues and Eigenvectors

- Symmetric matrices

$$\mathbf{A} \in \mathbb{R}^{n \times n} : \mathbf{A}^T = \mathbf{A} \quad \text{or} \quad \mathbf{A} \in \mathbb{C}^{n \times n} : \mathbf{A}^H = \mathbf{A}$$

$$\mathbf{A} = \begin{bmatrix} -1 & -2 & 1 \\ -2 & 2 & 3 \\ 1 & 3 & 1 \end{bmatrix} \quad \mathbf{A} = \begin{bmatrix} -1 & j & 7 \\ -j & 2 & 2-j \\ 7 & 2+j & 1 \end{bmatrix}$$

$$\begin{aligned} \mathbf{A}\mathbf{v} = \lambda \mathbf{v} \Rightarrow \lambda \|\mathbf{v}\|_2^2 &= \mathbf{v}^H (\lambda \mathbf{v}) = \mathbf{v}^H \mathbf{A} \mathbf{v} = \mathbf{v}^H \mathbf{A}^H \mathbf{v} = (\mathbf{A}\mathbf{v})^H \mathbf{v} = \bar{\lambda} \|\mathbf{v}\|_2^2 \\ \Rightarrow \lambda &= \bar{\lambda} \Rightarrow \lambda \in \mathbb{R} \end{aligned}$$

$$\begin{cases} \mathbf{A}\mathbf{v}_1 = \lambda_1 \mathbf{v}_1 \\ \mathbf{A}\mathbf{v}_2 = \lambda_2 \mathbf{v}_2 \end{cases} \Rightarrow \lambda_2 \mathbf{v}_1^H \mathbf{v}_2 = \mathbf{v}_1^H \mathbf{A} \mathbf{v}_2 = (\mathbf{A}\mathbf{v}_1)^H \mathbf{v}_2 = \lambda_1 \mathbf{v}_1^H \mathbf{v}_2 \\ \Rightarrow \mathbf{v}_1^H \mathbf{v}_2 = 0 \Rightarrow \langle \mathbf{v}_1, \mathbf{v}_2 \rangle = 0$$

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# Eigenvalues and Eigenvectors

- Symmetric matrices

$$\mathbf{A} \in \mathbb{R}^{n \times n} : \mathbf{A}^T = \mathbf{A} \quad \text{or} \quad \mathbf{A} \in \mathbb{C}^{n \times n} : \mathbf{A}^H = \mathbf{A}$$

$$\left\{ \begin{array}{l} \lambda_1 \rightarrow \mathbf{v}_1 \\ \lambda_2 \rightarrow \mathbf{v}_2 \\ \vdots \\ \lambda_n \rightarrow \mathbf{v}_n \end{array} , \quad \lambda_i \in \mathbb{R} , \quad \langle \mathbf{v}_i, \mathbf{v}_j \rangle = \mathbf{v}_i^H \mathbf{v}_j = \delta[i-j] \right.$$

$$\begin{aligned} \mathbf{V} = [\mathbf{v}_1, \dots, \mathbf{v}_n] \Rightarrow \mathbf{AV} &= [\underbrace{\mathbf{Av}_1}_{\lambda_1 \mathbf{v}_1}, \dots, \underbrace{\mathbf{Av}_n}_{\lambda_n \mathbf{v}_n}] = \mathbf{V} \begin{bmatrix} \lambda_1 & 0 & \dots & 0 \\ 0 & \lambda_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \lambda_n \end{bmatrix} \\ \mathbf{V}^H \mathbf{V} &= \mathbf{I}_{n \times n} = \mathbf{V} \mathbf{V}^H \end{aligned}$$

$$\Rightarrow \mathbf{A} \underbrace{\mathbf{V} \mathbf{V}^H}_{\mathbf{I}_{n \times n}} = \mathbf{A} = \mathbf{V} \operatorname{diag}(\lambda_1, \dots, \lambda_n) \mathbf{V}^H$$

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# Eigenvalues and Eigenvectors

- Symmetric matrices

$$\mathbf{A} \in \mathbb{R}^{n \times n} : \mathbf{A}^T = \mathbf{A} \quad \text{or} \quad \mathbf{A} \in \mathbb{C}^{n \times n} : \mathbf{A}^H = \mathbf{A}$$

$$\mathbf{V} = [\mathbf{v}_1, \dots, \mathbf{v}_n], \quad \mathbf{A} = \mathbf{V} \underbrace{\text{diag}(\lambda_1, \dots, \lambda_n)}_{\Lambda} \mathbf{V}^H$$

$$\begin{aligned} \mathbf{x} \in \mathbb{C}^{n \times 1} \Rightarrow \frac{\mathbf{x}^H \mathbf{A} \mathbf{x}}{\mathbf{x}^H \mathbf{x}} &= \frac{\mathbf{x}^H \mathbf{V} \Lambda \mathbf{V}^H \mathbf{x}}{\mathbf{x}^H \mathbf{V} \mathbf{V}^H \mathbf{x}} = \frac{(\mathbf{V}^H \mathbf{x})^H \Lambda (\mathbf{V}^H \mathbf{x})}{(\mathbf{V}^H \mathbf{x})^H (\mathbf{V}^H \mathbf{x})} \\ &= \frac{\sum_{i=1}^n \lambda_i |\langle \mathbf{v}_i, \mathbf{x} \rangle|^2}{\sum_{i=1}^n |\langle \mathbf{v}_i, \mathbf{x} \rangle|^2} \end{aligned}$$

$$\Rightarrow \boxed{\lambda_{\min} \leq \frac{\mathbf{x}^H \mathbf{A} \mathbf{x}}{\mathbf{x}^H \mathbf{x}} \leq \lambda_{\max}}$$



# Eigenvalues and Eigenvectors

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$$\lambda_1 \leq \lambda_2 \leq \dots \leq \lambda_n$$

Min-Max Theorem:

$$\left\{ \begin{array}{l} \lambda_i = \min_{\substack{\mathcal{U} \\ \dim(\mathcal{U})=i}} \left( \max_{0 \neq \mathbf{x} \in \mathcal{U}} \frac{\mathbf{x}^H \mathbf{A} \mathbf{x}}{\mathbf{x}^H \mathbf{x}} \right) \\ \lambda_i = \max_{\substack{\mathcal{U} \\ \dim(\mathcal{U})=n-i+1}} \left( \min_{0 \neq \mathbf{x} \in \mathcal{U}} \frac{\mathbf{x}^H \mathbf{A} \mathbf{x}}{\mathbf{x}^H \mathbf{x}} \right) \end{array} \right.$$