

## Matrix Norms

What norms would we apply to matrices?

$$\text{basis } U = (\vec{u}_1, \vec{u}_2, \vec{u}_3)$$


$$\text{basis } V = (\vec{v}_1, \vec{v}_2, \vec{v}_3)$$

$$\begin{pmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \end{pmatrix} = A \begin{pmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \end{pmatrix}$$

$$x = \alpha_1 u_1 + \alpha_2 u_2 + \alpha_3 u_3$$

$$y = \beta_1 v_1 + \beta_2 v_2 + \beta_3 v_3$$

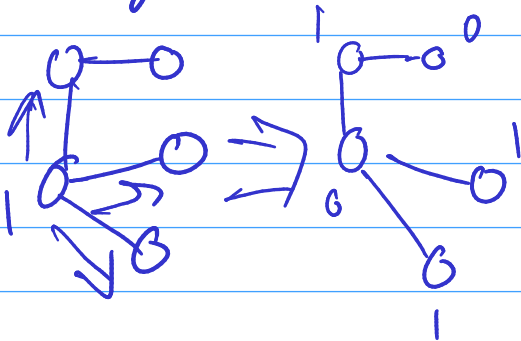
Alternative

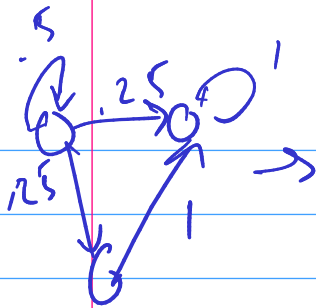
$$y = Ax \quad f(x)$$


$$y_i = \sum_j a_{ij} x_j$$

Matrix-vector mult.  
with adjacency matrix  $A$

$$x = \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}$$





$A$

$k$ -steps 1 step  $\downarrow$

$$\begin{pmatrix} p_1 \\ p_2 \\ p_3 \end{pmatrix}$$

$$\begin{pmatrix} p_1 \\ p_2 \\ p_3 \end{pmatrix}$$

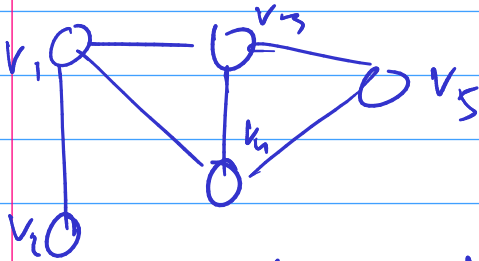
$A^k$

$$A^k x = \underbrace{A \cdots A}_{k \text{ times}} (Ax)$$

$k$ -times

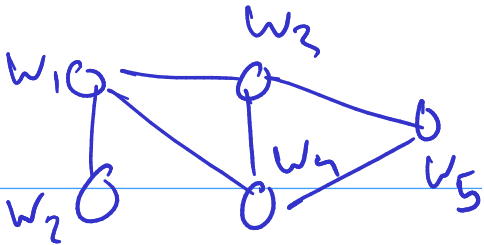
$$\begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}$$

# Laplacian's matrix



adjacency matrix  $A$  |  $L = D - A$   
degrees  $D$

$$w = L \cdot v$$

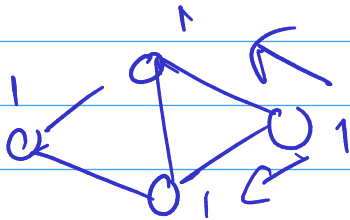


$$w = Dv - Av$$

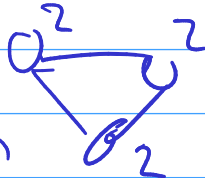
$$w_i = Dv_i - \sum_j A_{ij} v_j$$

$$\vec{w}_0 = Dv_i - \sum_j A_{ij} v_j \quad \uparrow \text{ if } j \text{ is on } i$$

$$\text{if } Lv = 0$$



$$3v_2 = v_1 + v_3 + v_4$$



$$0 = (v_1 - v_2) + (v_3 - v_2) + (v_4 - v_2)$$



## Demo: Matrix norms

### In-class activity: Matrix norms

induced "p-norms"

$$\|A\|_2 = \max_{\|x\|_2=1} \|Ax\|_2$$

$$= \max_x \frac{\|Ax\|_2}{\|x\|_2}$$

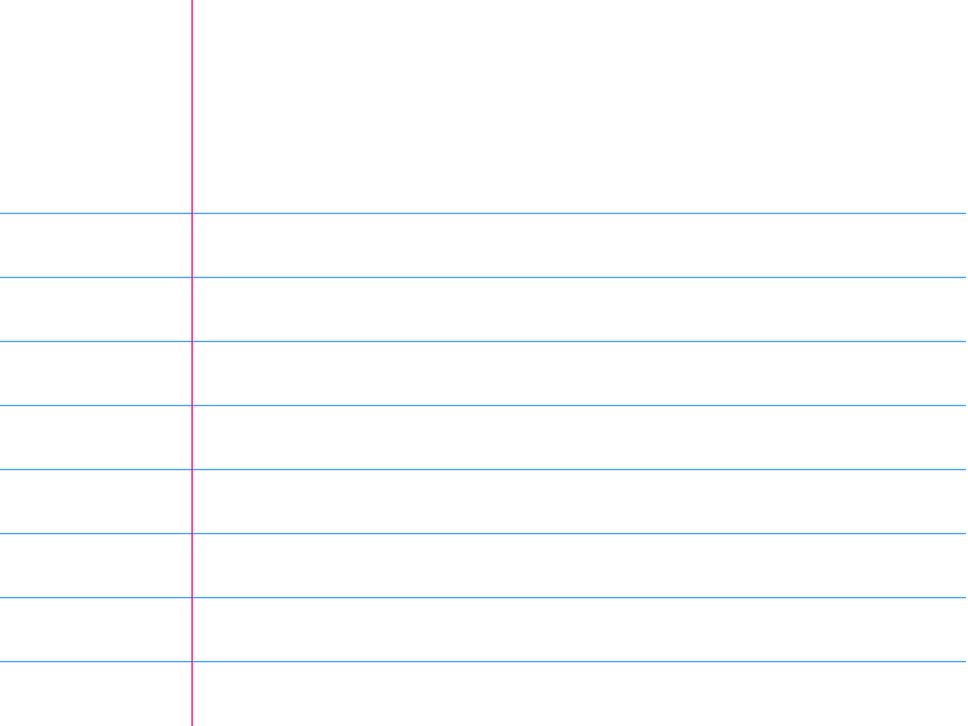
Aside: if  $A$  is sym.

maximizer  $x$  of  $\|Ax\|_2$

will be the eigenvector

with the largest eigenvalue

$\|A\|_2 =$  largest eig<sup>value</sup> of  $A$   
in abs.



# Properties of Matrix Norms

Matrix norms inherit the vector norm properties:

1.  $\|A\| > 0 \Leftrightarrow A \neq \mathbf{0}$ .
2.  $\|\gamma A\| = |\gamma| \|A\|$  for all scalars  $\gamma$ .
3. Obeys triangle inequality  $\|A + B\| \leq \|A\| + \|B\|$

nonnegative

and zero only if  $A=0$

But also some more properties that stem from our definition:

$$\|A x\|_p \leq \|A\|_p \|x\|_p \quad \text{of } p\text{-norm}$$

submultiplicative

$$\|AB\|_p \leq \|A\|_p \|B\|_p$$

$$\|Ax\|_F \leq \|A\|_F \|x\|_F$$

$$\| \| \begin{bmatrix} \rho_{11} & & \\ & \rho_{22} & \\ & & \rho_{33} \end{bmatrix} \| \|_2$$

$$\max \|X\| = \| \| \begin{bmatrix} \rho_{11} & & \\ & \rho_{22} & \\ & & \rho_{33} \end{bmatrix} X \| \|_2$$

$$\max_{\|x\|=1} \left\| \begin{pmatrix} D_{11}x_1 \\ D_{22}x_2 \\ D_{33}x_3 \end{pmatrix} \right\|_2$$

$$\max_{\|x\|=1} \sqrt{(D_{11}x_1)^2 + (D_{22}x_2)^2 + (D_{33}x_3)^2}$$

$$\sqrt{(\max_i D_{ii} \cdot 1)^2} = \max_i D_{ii}$$

$$\| \begin{bmatrix} D_{11} & & \\ & D_{22} & \\ & & D_{33} \end{bmatrix} \|_{\infty} = \max \{ |D_{11}|, |D_{22}|, |D_{33}| \}$$

max

$$\|x\|_{\infty} = 1$$

$$x = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} \text{ or } \begin{bmatrix} 1 \\ -1 \\ 1 \end{bmatrix}$$

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

$$\|A\|_1 = \max_{\|x\|_1=1} Ax$$

if  $x_i = \alpha$

$$\sum_{i=1}^n |x_i| = 1 \quad x = \begin{pmatrix} \alpha \\ \alpha \\ \vdots \\ \alpha \end{pmatrix} \quad \|A\|_1 = \max_j \sum_i |A_{ij}|$$



## Example: Orthogonal Matrices

What is the 2-norm of an orthogonal matrix?

$Q$  is orthogonal

$$Q^T Q = I$$



$$\max_{\|x\|=1} \|Qx\|_2 = \max_{\|x\|=1} \sqrt{(Qx)^T \cdot Qx}$$

$$\|y\|_2^2 = y^T y$$

$$\|Q\|_2 = \max_{\|x\|_2=1} \sqrt{(Qx)^T \cdot Qx}$$

$$= \max_{\|x\|_2=1} \sqrt{x^T \underbrace{Q^T Q}_I x}$$

$$= \max_{\|x\|_2=1} \sqrt{x^T x} = 1$$

$$\|y\|_2^2 = y^T y$$

$$= \sum_i |y_i|^2$$

$$\|y\|_2 = \sqrt{y^T y}$$

## Conditioning

Now, let's study condition number of solving a linear system

$$Ax = b.$$

$x = ?$  given  $b$

$$A(x + \Delta x) = b + \Delta b$$

output error

input error

$$\text{rel error} = \frac{\|\Delta x\| \|b\|}{\|Ab\| \|x\|}$$

$$\text{rel error} = \frac{\text{rel error in out.}}{\text{rel error in input}}$$

$$= \frac{\|\Delta x\| / \|x\|}{\|\Delta b\| / \|b\|}$$

$$\text{rel. err} = \frac{\|Ax\| \|b\|}{\|Ab\| \|x\|}$$

$$= \frac{\|A^{-1}Ab\| \|Ax\|}{\|Ab\| \|x\|}$$

$$\leq \|A^{-1}\| \cdot \|A\| = \underbrace{\frac{\|Ab\| \|x\|}{\|Ab\| \|x\|}}_1$$

$$\text{rel err} = \frac{\|A^{-1}Ab - Ax\|}{\|Ax\|} = \frac{\|b\|}{\|Ax\|}$$

$$= \frac{\|A^{-1} \cdot Ab\| \cdot \|Ax\|}{\|Ax\| \cdot \|Ax\|}$$

$$= \frac{\|A^{-1}\| \|A\| \|Ab\| \|x\|}{\|Ab\| \|x\|}$$

$$= \underbrace{\|A^{-1}\| \|A\|}_{\kappa(A)}$$

$$y = Ax$$

$$(y + \Delta y) = A(x + \Delta x)$$

$$y + \Delta y = Ax + \Delta x + A\Delta x$$

True is  $x$

error is  $\Delta x$

bound  $\Delta y$  with resp.  $y$

worst case:  $\Delta x$  magnified  
must

$$\Delta y = A\Delta x$$

$x$  magnified least



**Demo:** Condition number visualized

**Demo:** Conditioning of  $2 \times 2$  Matrices