

## First Eigenvalue & Eigenvector

Recall:

$\lambda, \vec{v}$  is an eigenvalue & corresponding eigenvector of an  $n \times n$  matrix  $A$  if:

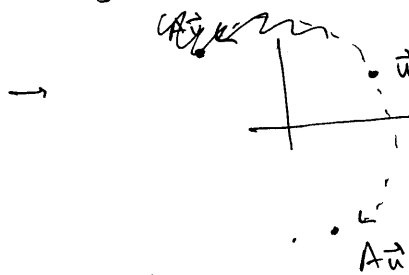
$$A\vec{v} = \lambda\vec{v}$$

$$\Rightarrow (A - \lambda I)\vec{v} = 0$$

$\Rightarrow \det(A - \lambda I) = 0$   $\leftarrow$  this is a polynomial in  $\lambda$ , known as the characteristic polynomial  $\chi(\lambda)$ .

Eigenvalues of real matrix may be complex:

Ex:  $A = \begin{pmatrix} 0 & 1 \\ -1 & 0 \end{pmatrix}$



rotation.

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

$$\chi(\lambda) = \lambda^2 + 1$$

$\Rightarrow \lambda = \pm i$   $\leftarrow$  complex conjugate.

$$\Rightarrow \begin{pmatrix} i & 1 \\ -1 & i \end{pmatrix} \vec{v}_1 = 0 \Rightarrow \vec{v}_1 = \begin{pmatrix} i \\ 1 \end{pmatrix}$$

$$\Rightarrow \begin{pmatrix} -i & 1 \\ -1 & -i \end{pmatrix} \vec{v}_2 = 0 \Rightarrow \vec{v}_2 = \begin{pmatrix} -i \\ 1 \end{pmatrix}$$

complex conjugate.

Since  $\text{If } A \text{ is real,}$

$$A\vec{v}_1 = \lambda_1 \vec{v}_1$$

$$\Rightarrow A\vec{v}_1 = \bar{\lambda}_1 \vec{v}_1$$

$\text{If } \vec{v}_1 \text{ is eigenvector,}$   
so is  $\vec{v}_1$ .

How to we find eigenvals / eigenvectors without solving polynomial equations

$\lambda$  Multiplicity  $\lambda$  may be a repeated root of  $\chi(\lambda) \rightarrow$  then find basis for the eigenspace.

The dimension of the eigenspace may or may not be the same as the multiplicity of  $\lambda$ :

Ex:  $A = \begin{pmatrix} 1 & k \\ 0 & 1 \end{pmatrix}$  (shear matrix)

$\chi(\lambda) = (1-\lambda)(1-\lambda) = 0 \Rightarrow \lambda = 1$

$A - \lambda I = \begin{pmatrix} 0 & k \\ 0 & 0 \end{pmatrix} \Rightarrow (A - \lambda I)\vec{v} = 0 \Rightarrow \vec{v} = \begin{pmatrix} 1 \\ 0 \end{pmatrix}$  only one eigenvector.

Diagonalizable Matrix If  $A$  has  $n$  ~~distinct~~ linearly independent eigenvectors, then it is diagonalizable:

Let  $V = (\vec{v}_1 \dots \vec{v}_n)$ . Then  $AV = \Lambda V$ , and

since  $V$  is invertible,  $A = V\Lambda V^{-1}$ , or likewise:

$\Lambda = V^{-1}AV$  ← similarity transform

rows are left eigenvectors, columns are right eigenvectors

preserves eigenvals.

Best <sup>almost</sup> case for <sup>numerical</sup> Linear algebra:  $A$  is real-symmetric  
(best case would be real symmetric positive definite).

$$\Rightarrow A^t = A, A^r = A.$$

$\Rightarrow$  Eigenvalues are real, and  $A$  is diagonalized by an orthogonal matrix:  $Q$ .

~~Pf. Let  $\lambda, \vec{v}$  be eigenvalue/vector pair.  
 $A\vec{v} = \lambda\vec{v}$   
 $A^t\vec{v} = \lambda\vec{v}$~~

Pf.: Let  $\vec{u}, \vec{v}$  correspond to two eigenvals,  $\lambda_1, \lambda_2$ .

Then  ~~$(A\vec{u}, \vec{v}) = (\lambda_1\vec{u}, \vec{v}) = \lambda_1(\vec{u}, \vec{v})$~~

but also  ~~$(A\vec{u}, \vec{v}) = (\vec{u}, A\vec{v}) = \lambda_2(\vec{u}, \vec{v})$~~

$$\Rightarrow (A\vec{u}, \vec{v}) - (A\vec{u}, \vec{v}) = 0 = (\lambda_1 - \lambda_2)(\vec{u}, \vec{v})$$

$$\Rightarrow (\vec{u}, \vec{v}) = 0 \text{ since } \lambda_1 \neq \lambda_2 \text{ (by assumption).}$$

What if  $A$  does not have  $n$  lin. indep. eigenvals?

$\Rightarrow$  Jordan form instead of diag. diagonal form.

What we mean is:

Instead of  $A$  being similar to a diagonal matrix,  $W^{-1}AW = D, A$ .

is similar to one in Jordan form:

For some  $W$ ,  $W^{-1}AW = J$ , with

$$J = \begin{pmatrix} J_1 & & \\ & \ddots & \\ & & J_m \end{pmatrix}, \quad J_i = \begin{pmatrix} \lambda_i & 1 & & \\ & \lambda_i & \ddots & \\ & & \ddots & 1 \\ & & & \lambda_i \end{pmatrix}$$

- # blocks = # linearly independent eigenvectors  
~~size of block~~

[ This form is unstable for small changes in the entries of  $A$  or  $J$ .

~~For~~ In general, what can we say about the eigenvalues of a particular matrix? How do we calculate them? (Why do we care?)

Ex: ODE IVP:

$$\vec{y}' = A \vec{y}$$

is equivalent (under a change of variables) to

the system:

~~$$\vec{y}' = A \vec{y}$$~~

$$\vec{u}' = D \vec{u}$$

↑  
 diagonal:  $\begin{pmatrix} \lambda_1 & & \\ & \ddots & \\ & & \lambda_n \end{pmatrix}$  eigenvalues of  $A$ .

Gerschgorin's Theorem

Let  $A$  be an  $n \times n$  matrix (real or complex). Then all the eigenvalues of  $A$  lie in  $\bigcup_i D_i$ , with

$$D_i = \left\{ z \in \mathbb{C} \text{ s.t. } |z - a_{ii}| \leq \underbrace{\sum_{j \neq i} |a_{ij}|}_{\text{sum of off-diagonal entries of row } i} \right\}$$

( $D_i$  is a "Gerschgorin Disk")

If  $m$  discs are connected, then  $m$  eigenvalues are located in this region.

Pf: Let  $\lambda, \vec{v}$  be an eigenvalue/vector pair.

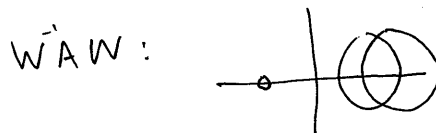
Then  $A\vec{v} = \lambda\vec{v} \Rightarrow \sum_j a_{ij}v_j = \lambda v_i$  (for all  $i$ )

$$\Rightarrow (\lambda - a_{ii})v_i = \sum_{j \neq i} a_{ij}v_j$$

pick largest entry of  $\vec{v}$ ,  $v_k$   $\Rightarrow (\lambda - a_{kk})v_k = \sum_{j \neq k} a_{kj}v_j$

$$|\lambda - a_{kk}| \leq \sum_{j \neq k} |a_{kj}| \frac{|v_j|}{|v_k|} \leq \sum_{j \neq k} |a_{kj}|$$

The trick you can play:



# The power method

Goal: Calculate the largest eigenpair

(Assume  $A$  is diagonalizable)

Start with random vector  $\vec{w} = \sum c_j \vec{v}_j$

Then  $A\vec{w} = \sum c_j A\vec{v}_j = \sum c_j \lambda_j \vec{v}_j$

$$\Rightarrow A^k \vec{w} = \sum c_j \lambda_j^k \vec{v}_j \approx c_1 \lambda_1^k \vec{v}_1 \text{ for sufficiently large } k.$$

IP  $\lambda_1 > \lambda_2$  (sufficiently) then  $\lambda_1$  dominates.

Normalize on each step:

$$\vec{w}_0 = \vec{w} / \|\vec{w}\|$$

$$\vec{w}_k = \frac{A\vec{w}_{k-1}}{\|A\vec{w}_{k-1}\|} \rightarrow \text{eigenvector.}$$

To calculate  $\lambda_k$ ,

①  $w_{ki} / w_{(k-1)i}$  (but could be small)

② set  $\lambda_k^{(k)} = (A\vec{w}_{k-1}, \vec{w}_{k-1})$  (since  $\|\vec{w}_{k-1}\| = 1$ )

The rate of convergence is roughly:

$$\|\vec{v}^{(k)} - \vec{v}\| \approx O\left(\left(\frac{\lambda_2}{\lambda_1}\right)^k\right)$$