

## ⑧ Eigen values

$$A \in \mathbb{R}^{n \times n}$$

$x$  is an eigenvector of  $A$  :

[ eigenvectors unique?  
No.

$$x \neq 0, \text{ there is a } \lambda \text{ so that } Ax = \lambda x$$

$\lambda$  eigenvalue of  $A$

[ must  $A$  be square?

$$\Leftrightarrow (A - \lambda I)x = 0 \text{ has a solution } x \neq 0$$

Yes.

$$\Leftrightarrow N(A - \lambda I) \neq \{0\}$$

$$\begin{pmatrix} 1 & x & x & x & x \\ & 2 & & & \\ & & 3 & & \\ & & & 4 & \\ & & & & 7 \end{pmatrix}$$

For  $\nabla$  matrices, eigen values appear on the diagonal.

Because eigenvalues satisfy a polynomial equation of degree  $n$ , and because there is no formula to solve such equations, num. methods for eigenvalues must be approximate!

## What matrix operations do to eigenvalues

Suppose  $Ax = \lambda x$ .

- "Scaling"  $\beta A \rightsquigarrow (\beta A)x = \beta \lambda x$
- "Shift"  $A - \sigma I \rightsquigarrow (A - \sigma I)x = Ax - \sigma x = (\lambda - \sigma)x$
- Power  $A^k \rightsquigarrow A^k x = \lambda^k x$
- Inverse  $A^{-1} \rightsquigarrow Ax = \lambda x \rightsquigarrow \frac{1}{\lambda}x = A^{-1}x$
- Similarity  $T^{-1}AT \rightsquigarrow y := T^{-1}x$

$$\begin{aligned}(T^{-1}AT)y &= T^{-1}Ax \\ &= \lambda T^{-1}x \\ &= \lambda y\end{aligned}$$

$\rightsquigarrow$  Similarity transforms preserve eigenvalues  $\triangle$

Will also say:  $A, B$  are similar if there exists

a matrix  $T$  such that  $B = T^{-1}AT$ .

If  $A$  is similar to a diagonal matrix, it's called

Diagonalizable.

Let  $X = (|||)$  be a matrix full of linearly independent eigenvectors. Then

$$AX = X \underbrace{\begin{pmatrix} \lambda_1 & & \\ & \ddots & \\ & & \lambda_n \end{pmatrix}}_{\mathbb{D}} \leadsto X^{-1}AX = \mathbb{D}.$$

So that would do it (= diagonalize a matrix).

$$\text{algebraic multiplicity} \geq \text{geometric multiplicity}$$

(multiplicity of  $\lambda$   
as a root of the  
characteristic polynomial)

(# of lin. indep.  
eigenvectors  
corresponding to  $\lambda$ )

Defective matrix has eigenvalue with

$$AM > GM.$$

Defective matrices are not diagonalizable.

Diagonalizable matrices are not defective.

Tool: Schur form

Every matrix is orthogonally similar to an upper triangular matrix.

$$A = QUQ^T$$

If we knew how to compute this, why would it be helpful for knowing eigenvalues? *on the diagonal of U.*

Power iteration

Eigenvalues of  $A^{20,000}$ ?

$$|\lambda_1| > |\lambda_2| > \dots$$

$$\begin{array}{cc} \uparrow & \uparrow \\ x_1 & x_2 \end{array}$$

Assume  $\|x_1\| = 1$

$$y = A^{20,000} (\underbrace{\alpha x_1 + \beta x_2}_x) = \alpha \lambda_1^{20,000} x_1 + \beta \lambda_2^{20,000} x_2$$

$$\frac{y}{\lambda_1^{20,000}} = \alpha x_1 + \beta \underbrace{\left(\frac{\lambda_2}{\lambda_1}\right)^{20,000}}_{\ll 1}$$

Possible problems:

- starting vector has no component for  $\lambda_1$  *no problem because of rounding*
- $\lambda_1 = \lambda_2$

Demo: Power iteration and variants

Power it.

$$x_{k+1} = Ax_k$$

Normalized power it.

$$x_{k+1} = \frac{Ax_k}{\|Ax_k\|} \quad \leftarrow \text{fixes overflow issue}$$

Inverse iteration:

$$x_{k+1} = \frac{A^{-1}x_k}{\|A^{-1}x_k\|} \quad \leftarrow \text{finds eigens of smallest eigenvalue (by magnitude)}$$

Inverse iteration w/shift

$$x_{k+1} = \frac{(A - \sigma I)^{-1}x_k}{\|(A - \sigma I)^{-1}x_k\|} \quad \leftarrow \text{finds eigenvalues near } \sigma$$

Rayleigh quotient iteration: set  $\sigma$  to the Rayleigh quotient in inv. it. w/shift.

The Rayleigh quotient is an estimate of the eigenvalue for an approx. eigenvector  $x$ :

$$\frac{x \cdot Ax}{x \cdot x}$$

$\leftarrow$  what if  $Ax = \lambda x$  exactly?

[Downside of all these methods? One eigenvector at a time.

Idea: Just iterate multiple vectors at a time.

$\rightarrow$  "Simultaneous iteration"

o [Why doesn't that work?  $\rightarrow$  all vectors converge to the eigenvector for  $\lambda_1$  (the largest by magnitude)

Idea: Keep them linearly independent. Even better: keep them orthogonal!

## Orthogonal iteration

$$X_0 \in \mathbb{R}^{n \times p} \quad (p \leq n) \text{ arbitrary (ideally w/full rank)}$$

$$Q_1 R_1 = X_0$$

$$X_1 = A Q_1$$

$$Q_2 R_2 = X_1$$

$$X_2 = A Q_2$$

$\vdots$

Suppose this "converges" so that  $X_{k+1} \approx X_k$ .

$$\leadsto Q_{k+1} R_{k+1} = X_k \approx X_{k+1}$$

$$\leadsto X_{k+1} = A Q_{k+1}$$

$$\leadsto Q_{k+1} R_{k+1} = A Q_{k+1}$$

$$\leadsto Q_{k+1} R_{k+1} Q_{k+1}^T = A \quad \leftarrow [?] \quad \text{Schur form!}$$