

The spectral theorem

MATH 6610 Lecture 08

September 21, 2020

Eigenvalues/eigenvectors



Trefethen & Bau: Lecture 24

Diagonalizability

L08-S01

Recall:

- All non-defective square matrices are diagonalizable (eigenvalue decomposition) ✓
- All square matrices are bidiagonalizable (Jordan normal form)
- All square matrices are unitarily triangularizable (Schur decomposition)
nonzeros on main, super-diagonal.

A triangular: $A = \begin{pmatrix} \nabla \\ 0 \end{pmatrix}$ (upper triangular)

EVD decomposition: $SAS^{-1} = \begin{pmatrix} \diagdown & 0 \\ 0 & \diagdown \end{pmatrix}$

Jordan normal form: $SAS^{-1} = \begin{pmatrix} \diagdown & & \\ & \diagdown & \\ & & \diagdown \end{pmatrix}$

Schur decomp:
 $UAU^* = \begin{pmatrix} \nabla \\ 0 \end{pmatrix}$

Recall:

- All non-defective square matrices are diagonalizable (eigenvalue decomposition)
- All square matrices are bidiagonalizable (Jordan normal form)
- All square matrices are unitarily triangularizable (Schur decomposition)

When are matrices unitarily diagonalizable?

$$U^*AU = \begin{pmatrix} \lambda_1 & & 0 \\ & \ddots & \\ 0 & & \lambda_n \end{pmatrix}$$

The spectral theorem

Definition

A matrix $A \in \mathbb{C}^{n \times n}$ is a *normal matrix* if it commutes with its transpose.

$$AA^* = A^*A$$

- 1.) Hermitian & skew-Hermitian matrices are normal
- 2.) Unitary matrices are normal ($UU^* = I = U^*U$)
- 3.) There are normal matrices that don't fit either of the above classifications

$$\begin{pmatrix} 1+i & 0 \\ 0 & -1-i \end{pmatrix} \quad \begin{pmatrix} 1 & 1 & 0 \\ 0 & 1 & 1 \\ 1 & 0 & 1 \end{pmatrix}$$

The spectral theorem

L08-S02

Definition

A matrix $A \in \mathbb{C}^{n \times n}$ is a *normal matrix* if it commutes with its transpose.

"For normal matrices"

Theorem (The spectral theorem)

A square matrix A is unitarily diagonalizable if and only if it is normal.

Proof: Assume A is unitarily diagonalizable:

$$A = U \Delta U^* \quad A^* = U \Delta^* U^*$$

$$AA^* = U \Delta \Delta^* U^*$$

$$A^*A = U \Delta^* \Delta U^*$$

} Also: $\Delta \Delta^* = \Delta^* \Delta$ (direct computation)

$$\Rightarrow A^*A = AA^* \\ (A \text{ is normal})$$

Assume A is normal. 2 steps ^{normal} \checkmark

(i) Reduce problem to analyzing upper triangular matrices

(ii) Show a normal, upper triangular matrix is diagonal.

(i) Schur decomposition: (HW)

$$A = U T U^*, \quad U \text{ unitary}$$

T : (upper) triangular

$$A \text{ is normal: } U T T^* U^* = \underline{A A^*} = \underline{A^* A} = U T^* T U^*$$

$$\Rightarrow T T^* = T^* T \quad (T \text{ is normal}) \quad \checkmark$$

(ii) T is normal and upper triangular.

$$T T^* = T^* T \implies (T T^*)_{i,i} = (T^* T)_{i,i} \\ i \in \{1, \dots, n\}$$

$$\begin{array}{ccc} (T T^*)_{i,i} & = & (T^* T)_{i,i} \\ \parallel & & \parallel \\ \underline{e_i^* T T^* e_i} & & e_i^* T^* T e_i \\ \parallel & & \parallel \\ \langle T^* e_i, T^* e_i \rangle & & \langle T e_i, T e_i \rangle \\ \parallel & & \parallel \end{array}$$

(e_i = vector of zeros, with entry 1 in i th place).

$$\underbrace{\|T^* e_i\|_2^2}_{\text{norm of } i\text{th row of } T}$$

$=$

$$\underbrace{\|T e_i\|_2^2}_{\text{norm of } i\text{th column of } T}.$$

$$T = \begin{pmatrix} \times & & & \\ & \times & & \\ & & \times & \\ & & & \times \end{pmatrix}$$

$i=1$: column 1 and row 1 of T have same norm.

\Rightarrow entries 2, ..., n in row 1 must be 0.

$$T = \begin{pmatrix} \times & & & \\ & \times & & \\ & & \times & \\ & & & \times \end{pmatrix}$$

$i=2$: column 2 and row 2 have same norm

\Rightarrow entries 3, ..., n in row 2 must be 0.

! continue (finite induction).

$\Rightarrow T$ is diagonal.

$A = U T U^*$, T is diagonal and U is unitary.

□

Normal matrices

Normal matrices are the class of matrices for which eigenvalues *precisely* characterize the action of a matrix.

Normal matrices

Normal matrices are the class of matrices for which eigenvalues *precisely* characterize the action of a matrix.

If A is normal, ...

- then the 2-norm induced operator, spectral radius, and maximum numerical range coincide

$$\|A\|_2 = \sup_{x \neq 0} \frac{\|Ax\|_2}{\|x\|_2}$$

$$\rho(A) = \max_j |\lambda_j|$$

$$W_A(\mathbb{C}) = \left\{ \frac{\langle Ax, x \rangle}{\langle x, x \rangle} \mid x \in \mathbb{C}^n \setminus \{0\} \right\}$$

Normal matrices

Normal matrices are the class of matrices for which eigenvalues *precisely* characterize the action of a matrix.

If A is normal, ...

- then the 2-norm induced operator, spectral radius, and maximum numerical range coincide
- then $\|Ax\|_2 = \|A^*x\|_2$ for any vector x

Normal matrices

Normal matrices are the class of matrices for which eigenvalues *precisely* characterize the action of a matrix.

If A is normal, ...

- then the 2-norm induced operator, spectral radius, and maximum numerical range coincide
- then $\|Ax\|_2 = \|A^*x\|_2$ for any vector x
- then $A = A^*U$ for some unitary U
- $\|A\|_F^2 = \sum_{i,j=1}^n |a_{i,j}|^2 = \sum_{j=1}^n |\lambda_j|^2$

Normal matrices

Normal matrices are the class of matrices for which eigenvalues *precisely* characterize the action of a matrix.

If A is normal, ...

- then the 2-norm induced operator, spectral radius, and maximum numerical range coincide
- then $\|Ax\|_2 = \|A^*x\|_2$ for any vector x
- then $A = A^*U$ for some unitary U

Actually, any of the above also implies that A is normal.

Eigenvalue conditioning

L08-S04
eigenvalue-computing map

Consider $A \in \mathbb{C}^{n \times n}$, along with the map $\lambda : \mathbb{C}^{n \times n} \rightarrow \mathbb{C}$ that computes an eigenvalue of A :

$$\underline{Av = \lambda(A)v}, \quad \text{for some } v \neq 0$$

What is the conditioning of this operation?

How sensitive is $A \mapsto \lambda(A)$ to perturbations in A ?

Eigenvalue conditioning

Consider $A \in \mathbb{C}^{n \times n}$, along with the map $\lambda : \mathbb{C}^{n \times n} \rightarrow \mathbb{C}$ that computes an eigenvalue of A :

$$Av = \lambda(A)v, \quad \text{for some } v \neq 0$$

What is the conditioning of this operation?

Theorem (Bauer-Fike)

Assume $A \in \mathbb{C}^{n \times n}$ is diagonalizable with eigenvector matrix $V \in \mathbb{C}^{n \times n}$. Then, using the 2-norm, the absolute condition number of computing eigenvalues is $\tilde{\kappa}_\lambda(A) = \kappa(V)$.

HW

$$V = \begin{pmatrix} | & & | \\ v_1 & \dots & v_n \\ | & & | \end{pmatrix}$$

eigenvectors.

$$\kappa(V) = \|V\|_2 \|V^{-1}\|_2$$

$$\tilde{\kappa}_\lambda(A) = \limsup_{\|SA\|_2 \leq \delta} \frac{\|\lambda(A+SA) - \lambda(A)\|_2}{\|SA\|_2}$$

$$\kappa(V)$$

If T is normal: $K(V) = 1$ ($\|W\|_2 = \|V^{-1}\|_2 = 1$)

$$\Rightarrow \tilde{K}_\lambda(A) = 1$$