

16B. Prof. ANAND SAHA

Announce: Remember Redo  
Self-Grades  
& HW 9 on regular schedule

Today: Finish Upper-triangularization story  
Understand consequences for stability  
Symmetric Matrix Case

Recall:  $\tilde{A} = U^T A U$  where  $U^T U = I$  since  $U_j$  is an orthonormal basis  
's columns

Upper-triangular:  $\tilde{A} = \begin{bmatrix} \lambda_1 & \dots & \dots \\ & \lambda_2 & \dots \\ & & \dots \\ & & & \lambda_n \end{bmatrix}$  'stuff'

Loose-end 1: What are the eigenvalues of  $\tilde{A}$ ? a) Are these the same as the eigenvalues of  $A$ ?

$\lambda_i$  is an eigenvalue of  $\tilde{A}$   
enters on the diagonal of  $\tilde{A}$ .

b) What are they?  
 $\lambda_i$ 's.

Check Consider  $\tilde{A} - \lambda I$ :  $\begin{bmatrix} \lambda_1 - \lambda & \dots & \dots \\ & \lambda_2 - \lambda & \dots \\ & & \dots \\ & & & \lambda_n - \lambda \end{bmatrix}$   
 $\tilde{A}_\lambda$

We know that for an eigenvalue  $\lambda$ , this matrix is not invertible.  
i.e. it has linearly dep columns.

Also we want if  $\lambda \neq \lambda_i$  for any  $i$ , then that  $\lambda$   
is not an eigenvalue.

In this case, none of the diagonal entries are zero.

Claim: This implies  $\tilde{A}_\lambda$  is invertible.

Why? Gaussian Elimination Succeeds! Can back-substitute  
to uniquely solve  
eqns  $\tilde{A}_\lambda \vec{x} = \vec{b}$   
Matrix can be inverted.

Other direction:

If  $\lambda = \lambda_i$  for some  $i$ , then  $\lambda$  is an eigenvalue

i.e.  $\tilde{A}_\lambda$  is not invertible if it has a 0 on the diagonal.

Why does having a zero on the diagonal imply linearly dep columns?

A: G.E. will get stuck. Won't find a pivot there.

$$\begin{bmatrix} \neq 0 & \text{stuff} \\ \neq 0 & \vdots \\ \circ & \dots \\ \vdots & \vdots \end{bmatrix}$$

Alternatively:

This  $i$ th column is a linear comb of the columns before it.  
Because we can solve for the weights by back substitution.

a) Are these  $\lambda_i$  the same eigenvalues as  $A$ ?

Characteristic poly

$$\begin{aligned} \det(\lambda I - \tilde{A}) &= \det(\lambda I - U^T A U) \\ &= \det(\lambda U^T U - U^T A U) \\ &= \det(U^T (\lambda I - A) U) \\ &= \det(U^T) \det(\lambda I - A) \det(U) \\ &= \det(\lambda I - A) \det(U^T) \det(U) \\ &= \det(\lambda I - A) \det(U^T U) \\ &= \det(\lambda I - A) \quad \leftarrow \det(I) = 1 \end{aligned}$$

Same characteristic poly  $\Rightarrow$  same eigenvalues.



So how does this help with BIBO stability?

Original System

$$\vec{x}[i+1] = A \vec{x}[i] + \vec{w}[i] \quad \leftarrow \|\vec{w}[i]\| \leq \epsilon$$

Claim: This is BIBO stable if all the eigenvalues of  $A$  have  $|\lambda| < 1$

We already proved it when  $A$  was diagonalizable.

Want to show  $\exists K$  s.t.  $\|\tilde{x}[i]\| \leq K \cdot \epsilon$ .

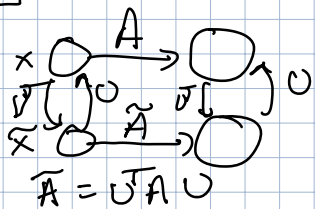
By Upper-triangularization (Schur Decomposition)

$\exists U$  s.t.  $\tilde{A} = U^T A U$  is upper triangular.

$$\tilde{A} = \begin{bmatrix} \lambda_1 & & & \\ & \lambda_2 & \beta_{2,3} & \\ & 0 & \ddots & \beta_{n,n-1} \\ & & & \lambda_n \end{bmatrix} \text{ stuff}$$

Change coordinates to  $\tilde{x} = U^T x$

$$\tilde{x}[i+1] = \tilde{A} \tilde{x}[i] + U^T \tilde{w}[i]$$



Call this  $\tilde{v}[i]$

$\|U^T \tilde{w}\|^2 = (U^T \tilde{w})^T (U^T \tilde{w}) \stackrel{B_3 \epsilon}{\leq} \epsilon$

$$= \tilde{w}^T U U^T \tilde{w}$$

$$= \tilde{w}^T \tilde{w} \quad \text{since } U U^T = I$$

$$= \|\tilde{w}\|^2$$

$\uparrow$  we know  $\|\tilde{v}[i]\| \leq \epsilon$

Is this bounded?  $\checkmark$  (Yes)

Use the philosophy of strong induction (Backwards)

Start at the end:

$$\tilde{x}_n[i+1] = \lambda_n \tilde{x}_n[i] + v_n[i]$$

Because  $|\lambda_n| < 1$ , This is BIBO stable.

$\exists$  constant  $K_n$  s.t.  $|\tilde{x}_n| \leq K_n \epsilon$ .

Base case Done.

Consider  $\tilde{x}_{n-1}$

$K$  in particular  $K_n = \frac{1}{1-|\lambda_n|}$

$$\tilde{x}_{n-1}(i+1) = \lambda_{n-1} \tilde{x}_{n-1}(i) + \left[ \beta_{n-1,n} \tilde{x}_n(i) + v_{n-1}(i) \right]$$

I know  $|\lambda_{n-1}| < 1$

I want to say  $\exists K_{n-1}$  s.t.  $|\tilde{x}_{n-1}| \leq K_{n-1} \epsilon$

To get what I want, I need  $\square$  to be bounded.

$$\text{But } \left| \beta_{n-1,n} \tilde{x}_n(i) + v_{n-1}(i) \right| \leq \left| \beta_{n-1,n} \right| \left| \tilde{x}_n(i) \right| + \left| v_{n-1}(i) \right|$$

$$\leq \left| \beta_{n-1,n} \right| \cdot K_n \epsilon + \epsilon$$

↑  
spectral number

$$\leq \left( \left| \beta_{n-1,n} \right| \cdot K_n + 1 \right) \epsilon$$

$$K_{n-1} = \left( \frac{1}{1 - |\lambda_{n-1}|} \right) \left( \left| \beta_{n-1,n} \right| \cdot K_n + 1 \right)$$

Assume  $\forall k$  in  $l+1, l+2, \dots, n$ ,

$$\text{we know } \exists K_k \text{ s.t. } \left| \tilde{x}_k(i) \right| \leq K_k \cdot \epsilon$$

Want to show  $\left| \tilde{x}_l(i) \right| \leq K_l \cdot \epsilon$ .

$$\tilde{x}_l(i+1) = \lambda_l \tilde{x}_l(i) + \left( \sum_{k=l+1}^n \beta_{l,k} \tilde{x}_k(i) \right) + v_l(i)$$

$$\text{So } \exists K_l = \left( \frac{1}{1 - |\lambda_l|} \right) \star \text{ is bounded by } \left( \sum_{k=l+1}^n \left| \beta_{l,k} \right| K_k + 1 \right) \epsilon \star$$

$$\tilde{A} = \begin{bmatrix} \lambda_1 & & & \\ & \lambda_2 & & \\ & & \beta_{i,j} & \\ 0 & & & \beta_{n,n} \\ & & & & \lambda_n \end{bmatrix} \leftarrow \text{stuff} = U^T A U$$

Recall  $U^T U = I$

How do we know that these  $\beta_{i,j}$  are well behaved?

Could these  $\beta_{i,j}$  be "ginormous"?  $\leftarrow$  Unreasonably large!

$$A = [\vec{a}_1 \ \vec{a}_2 \ \dots \ \vec{a}_n] \quad \rightarrow \boxed{\text{NO}} \quad \text{😊} \quad \text{😊}$$

Want to understand  $U^T A U$

First let's look at  $(U^T A) = [U^T \vec{a}_1 \ U^T \vec{a}_2 \ \dots \ U^T \vec{a}_n]$

$$\begin{aligned} \|U^T \vec{a}_i\|^2 &= \vec{a}_i^T U U^T \vec{a}_i = \vec{a}_i^T I \vec{a}_i \\ &= \vec{a}_i^T \vec{a}_i = \|\vec{a}_i\|^2 \\ &= \sum_{j=1}^n a_{ji}^2 \end{aligned}$$

Fact: The sum of squares of entries in  $U^T A$  is the same as the sum of squares of entries in  $A$ .

Definition The Frobenius Norm  $\|A\|_F^2 = \sum_{i,j} (a_{ij})^2$

Just prove: If  $U$  is orthogonal square matrix then

$$\|U A\|_F = \|A\|_F$$

From the definition:  $\|A\|_F = \|\tilde{A}\|_F$

$$\|\tilde{A}\|_F = \|U^T A U\|_F = \|(U^T A U)^T\|_F$$



Since  $\vec{u}_i$  is an eigenvector!

$$\begin{aligned} A\vec{u}_i &= U\Lambda U^T \vec{u}_i = U\Lambda \begin{pmatrix} 0 \\ \vdots \\ 1 \end{pmatrix} \leftarrow \text{id. part} \\ &= U \begin{pmatrix} 0 \\ \vdots \\ \lambda_i \end{pmatrix} = \lambda_i \vec{u}_i \end{aligned}$$

Any real symmetric matrix with all real eigenvalues has orthogonal eigenvectors and a full complement of them

Question: Must real symmetric matrices have real eigenvalues?

Will do this next time....