

**EECS 16B**

# **Designing Information Devices and Systems II**

## **Lecture 18**

Prof. Yi Ma

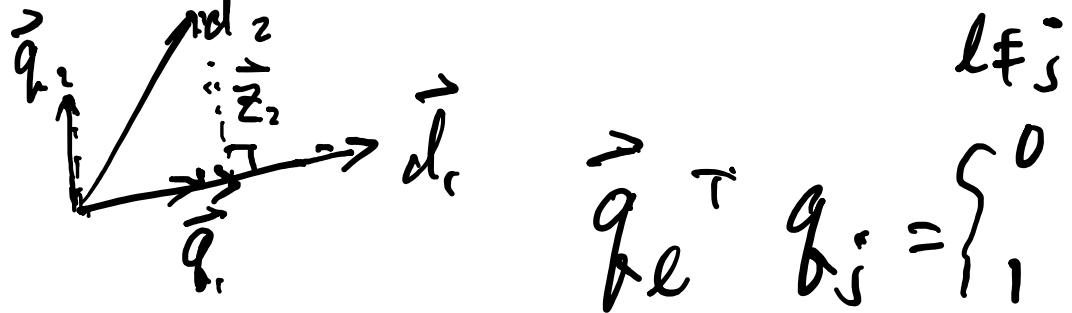
Department of Electrical Engineering and Computer Sciences, UC Berkeley,  
yima@eecs.berkeley.edu

# Outline

- Orthonormalization (Gram-Schmidt) and QR Decomposition
- Upper Triangularization

# Gram-Schmidt Procedure (Summary)

$$D = [\vec{d}_1, \vec{d}_2, \dots, \vec{d}_k]_{n \times k}$$



$$\begin{aligned} \vec{z}_1 &= \vec{d}_1 \\ \vec{z}_2 &= \vec{d}_2 - \frac{(\vec{d}_2^T \vec{q}_1) \vec{q}_1}{\|\vec{z}_2\|} \\ \rightarrow \vec{z}_3 &= \vec{d}_3 - \frac{(\vec{d}_3^T \vec{q}_1) \vec{q}_1}{\|\vec{z}_3\|} - \frac{(\vec{d}_3^T \vec{q}_2) \vec{q}_2}{\|\vec{z}_3\|} \\ &\vdots \end{aligned}$$

$$\begin{aligned} \vec{q}_1 &= \vec{z}_1 / \|\vec{z}_1\| \\ \vec{q}_2 &= \vec{z}_2 / \|\vec{z}_2\| \\ \vec{q}_3 &= \vec{z}_3 / \|\vec{z}_3\| \\ &\vdots \end{aligned}$$

$$\vec{z}_k = \vec{d}_k - \sum_{j=1}^{k-1} (\vec{d}_k^T \vec{q}_j) \vec{q}_j$$

$$\vec{q}_k = \vec{z}_k / \|\vec{z}_k\|$$

Claim: 1.  $\vec{z}_j^T \vec{q}_i = 0$  for all  $i < j$  2.  $\|\vec{z}_i\| = \vec{d}_i^T \vec{q}_i$

$$\begin{aligned} \textcircled{1} \quad \vec{z}_j^T \vec{q}_i &= \left( \vec{d}_j - \sum_{l=1}^{j-1} (\vec{d}_j^T \vec{q}_l) \vec{q}_l \right)^T \vec{q}_i \\ &= \vec{d}_j^T \vec{q}_i - (\vec{d}_j^T \vec{q}_i) = 0 \end{aligned}$$

②  $\|\vec{z}_j\|$

$$\vec{z}_j = \|\vec{z}_j\| \vec{q}_j$$

$$\vec{z}_j \cdot \vec{q}_j = \vec{d}_j^T \vec{q}_j - 0$$

$$\|\vec{z}_j\| = \vec{d}_j^T \vec{q}_j$$

# Gram-Schmidt & QR Decomposition $Q_{n \times k}^T x = 0$

$$\vec{d}_1 = (\vec{d}_1^T \vec{q}_1) \vec{q}_1$$

$$\vec{d}_2 = (\vec{d}_2^T \vec{q}_1) \vec{q}_1 + (\vec{d}_2^T \vec{q}_2) \vec{q}_2$$

$$\vec{d}_3 = (\vec{d}_3^T \vec{q}_1) \vec{q}_1 + (\vec{d}_3^T \vec{q}_2) \vec{q}_2 + (\vec{d}_3^T \vec{q}_3) \vec{q}_3$$

$$\vec{d}_k = (\vec{d}_k^T \vec{q}_1) \vec{q}_1 + (\vec{d}_k^T \vec{q}_2) \vec{q}_2 + \dots + (\vec{d}_k^T \vec{q}_k) \vec{q}_k$$

$\underbrace{\hspace{10em}}_{\|\vec{z}_k\|} \vec{q}_k$

$\downarrow \downarrow \quad (r_{ij} = \vec{d}_j^T \vec{q}_i)$

$$[\vec{d}_1, \vec{d}_2, \dots, \vec{d}_k] = [\vec{q}_1, \vec{q}_2, \dots, \vec{q}_k] \begin{bmatrix} r_{11} & r_{12} & \dots & r_{1k} \\ 0 & r_{22} & \dots & r_{2k} \\ \vdots & \ddots & \ddots & \vdots \\ 0 & \dots & 0 & r_{kk} \end{bmatrix}$$

$D_{n \times k} = Q_{n \times k} R_{k \times k}$

$R$

$$\underline{D_{n \times n}} = Q_{n \times n} R_{n \times n} \quad Q^T Q = I = Q Q^T - \text{orthogonal complete.}$$

$$\underline{D_{n \times k}} = \underline{Q_{n \times k}} R_{k \times k} \quad Q = [Q_{n \times k}, \tilde{Q}_{(n-k) \times k}] \quad \tilde{Q}^T Q_{n \times k} = 0$$

# QR, Diagonalization, Triangularization

QR Decomposition for  $D \in \mathbb{R}^{n \times k}$ :  $[\vec{d}_1, \vec{d}_2, \dots, \vec{d}_k] = [\vec{q}_1, \vec{q}_2, \dots, \vec{q}_k]$

$$\begin{bmatrix} r_{11} & r_{12} & \dots & r_{1k} \\ 0 & r_{22} & \dots & r_{2k} \\ \vdots & \ddots & \ddots & \vdots \\ 0 & \dots & 0 & r_{kk} \end{bmatrix}$$

$$y = Ax$$

$$D = QR \quad \left| \quad Q^T D = R \right.$$

Diagonalization for  $A \in \mathbb{R}^{n \times n}$ :

$$A[\vec{v}_1, \dots, \vec{v}_n] = [\lambda_1 \vec{v}_1, \dots, \lambda_n \vec{v}_n] = [\vec{v}_1, \dots, \vec{v}_n] \Lambda$$

$$AV = V\Lambda$$

$$V^{-1}AV = \Lambda$$

$$\begin{bmatrix} \lambda_1 & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & \lambda_n \end{bmatrix}$$

Triangularization for  $A \in \mathbb{R}^{n \times n}$ :  $A[\vec{u}_1, \vec{u}_2, \dots, \vec{u}_n] = [\vec{u}_1, \vec{u}_2, \dots, \vec{u}_n] T$

$$AU = UT$$

$$\begin{bmatrix} t_{11} & t_{12} & \dots & t_{1n} \\ 0 & t_{22} & \dots & t_{2k} \\ \vdots & \ddots & \ddots & \vdots \\ 0 & \dots & 0 & t_{nn} \end{bmatrix}$$

$$U^{-1}AU = T$$

$U$  - orthogonal  $T$

$$U^T A U = T$$

# Diagonalization v.s. Triangularization

Conditions for diagonalization of  $A \in \mathbb{R}^{n \times n}$ :  $V^{-1}AV = \underbrace{\begin{bmatrix} \lambda_1 & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & \lambda_n \end{bmatrix}}_{\Lambda}$  ←

$A \downarrow$   
 $AV = V\Lambda$  ←

$Av_i = \lambda_i v_i \quad i=1, \dots, n.$

$\begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} 1 \\ 0 \end{bmatrix} = 0 \cdot \begin{bmatrix} 1 \\ 0 \end{bmatrix}$

$\begin{bmatrix} \lambda & 1 \\ 0 & \lambda \end{bmatrix}$

Jordan  
 $\begin{bmatrix} \lambda & 1 & 0 & \dots & 0 \\ 0 & \lambda & 1 & 0 & \dots \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & \dots & 0 & \dots & \lambda \end{bmatrix} A$

$\underbrace{(A - \lambda I)}_{n \times n} v = \begin{bmatrix} 0 & 1 & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & \dots & 0 & \dots & 0 \end{bmatrix} v = 0$   
 $\begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$  ←

$Av = \lambda v$

$-P(\lambda) = 0$  ←

# Upper-Triangularization

~~$\det(\lambda I - A)$~~

Upper-triangularization for  $A \in \mathbb{R}^{n \times n}$ :  $U^{-1}AU =$

$$\begin{bmatrix} t_{11} & t_{12} & \dots & t_{1n} \\ 0 & t_{22} & \dots & t_{2n} \\ \vdots & \ddots & \ddots & \vdots \\ 0 & \dots & 0 & t_{nn} \end{bmatrix}$$

$z = U^{-1}x$

Eigenvalues of an upper-triangular matrix:

$x_{\{i+1\}} \neq A x_{\{i\}}$   
 $z_{\{i+1\}} = \underbrace{U^{-1}AU}_{\tilde{A}} z_{\{i\}}$

$\det(\lambda I - \tilde{A}) = \det(U) \det(\lambda I - \tilde{A}) \det(U^{-1})$

$= \det(U \lambda I U^{-1} - U \tilde{A} U^{-1})$

$= \det(\lambda I - A)$

$\det(\lambda I - T) = \det \begin{bmatrix} \lambda - t_{11} & & & \\ & \lambda - t_{22} & & \\ & & \ddots & \\ & & & \lambda - t_{nn} \end{bmatrix}$

$= (\lambda - t_{11}) \dots (\lambda - t_{nn})$

# Upper-Triangularization

Solution to an upper-triangular system of linear equations:

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} t_{11} & t_{12} & \cdots & t_{1n} \\ 0 & t_{22} & \cdots & t_{2n} \\ \vdots & \ddots & \ddots & \vdots \\ 0 & \cdots & 0 & t_{nn} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}$$

$$y = Ax$$

$$x = A^{-1}y$$

---

$$y_n = t_{nn} x_n \quad \leftarrow \quad x_n = t_{nn}^{-1} y_n$$

$$y_{n-1} = t_{n-1,n-1} x_{n-1} + \underbrace{t_{n-1,n} x_n}_{\text{known}} \quad \leftarrow \quad \underline{x_{n-1}}$$


$$\vdots$$
$$y_1 = t_{11} x_1 + \underline{\text{known}}$$



# Upper-Triangularization

Solution to an upper-triangular system of linear differential equations:

$$\dot{x}(t) = A x(t) + u(t)$$

$$\begin{bmatrix} \dot{x}_1(t) \\ \dot{x}_2(t) \\ \vdots \\ \dot{x}_n(t) \end{bmatrix} = \begin{bmatrix} t_{11} & t_{12} & \cdots & t_{1n} \\ 0 & t_{22} & \cdots & t_{2n} \\ \vdots & \ddots & \ddots & \vdots \\ 0 & \cdots & 0 & t_{nn} \end{bmatrix} \begin{bmatrix} x_1(t) \\ x_2(t) \\ \vdots \\ x_n(t) \end{bmatrix} + \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_n \end{bmatrix} u(t)$$


$$A = QR$$

$$Q^T \dot{x}(t) = R x(t) \quad \frac{dx_n(t)}{dt} = t_{nn} x_n(t) + b_n u(t)$$

$$x_n(t) = e^{t_{nn}(t-t_0)} x(t_0) + \int_{t_0}^t e^{t_{nn}(\tau-t_0)} b_n u(\tau) d\tau$$

$$\frac{dx_{n-1}(t)}{dt} = t_{n-1,n-1} x_{n-1}(t) + \underbrace{t_{n-1,n} x_n(t) + b_{n-1} u(t)}_{\tilde{u}_{n-1}(t)}$$

$$\frac{dx_1(t)}{dt} = t_{11} x_1(t) + \text{known}$$

# Upper-Triangularization (Schur Decomposition)

**Claim:** For any matrix  $A \in \mathbb{R}^{n \times n}$  with real eigenvalues, there exists an orthogonal matrix:  $U \in \mathbb{R}^{n \times n}$  such that  $U^T U = I$  and

$$T = U^{-1} A U = U^T A U = \begin{bmatrix} t_{11} & t_{12} & \cdots & t_{1n} \\ 0 & t_{22} & \cdots & t_{2k} \\ \vdots & \ddots & \ddots & \vdots \\ 0 & \cdots & 0 & t_{nn} \end{bmatrix}$$

$$\dot{x}(t) = A x(t)$$

Proof (by induction):

1.  $n = 1$   $A = (a_{11})$  true

$$z(t) = U^{-1} x(t)$$

$$x(t) = U z(t)$$

$\rightarrow$  2.  $n = k+1$   $A_{(k+1) \times (k+1)}$  can be triangulated if  $\forall A_{k \times k}$  can be triangulated

$$z(t) = U^T x(t)$$

---

$A \in \mathbb{R}^{(k+1) \times (k+1)}$   $A U = U T \begin{bmatrix} * & & \\ 0 & \times & \end{bmatrix}$   $A \vec{u}_1 = t_{11} \vec{u}_1$

# Upper-Triangularization (Schur Decomposition)

**Claim:** For any matrix  $A \in \mathbb{R}^{n \times n}$  with real eigenvalues, there exists an orthogonal matrix:  $U \in \mathbb{R}^{n \times n}$  such that  $U^T U = I$  and  $T = U^{-1} A U = U^T A U$  is upper-triangular.

Proof (continued):

$\vec{q}_1$  to be the eigenvector w.r.t.  $\lambda_1$  of  $A$   $k=1$   $A \vec{q}_1 = \lambda_1 \vec{q}_1$   $\leftarrow$  normal

$Q = [\vec{q}_1 \ \vec{q}_2 \ \dots \ \vec{q}_{k+1}]$  orthogonal  $Q^T Q = I$

$$Q^T A Q = \begin{bmatrix} \vec{q}_1^T \\ \vec{q}_2^T \\ \vdots \\ \vec{q}_{k+1}^T \end{bmatrix} \begin{bmatrix} \lambda_1 \vec{q}_1 & A \vec{q}_2 & \dots & A \vec{q}_{k+1} \end{bmatrix} = \begin{bmatrix} \lambda_1 & \tilde{a}_{12} & & \\ & \vdots & & \\ & & \tilde{A}_{k+1} & \\ & & & \ddots \end{bmatrix}$$

G.S.
 $\lambda_1$ 
 $\tilde{a}_{12}$ 
 $\tilde{A}_{k+1}$ 
 $\lambda_1 = A_{22}$ 
 $k+1$

# Upper-Triangularization (Schur Decomposition)

**Claim:** For any matrix  $A \in \mathbb{R}^{n \times n}$  with real eigenvalues, there exists an orthogonal matrix:  $U \in \mathbb{R}^{n \times n}$  such that  $U^T U = I$  and  $T = U^{-1} A U = U^T A U$  is upper-triangular.

Proof (continued):

$\tilde{A}_{22} \in \mathbb{R}^{k \times k}$  has  
real eigenvalues

$$\begin{aligned} \underline{\underline{\det(\lambda I - A)}} &= \underline{\underline{\det(\lambda I - \tilde{A})}} \\ &= \underline{(\lambda - \lambda_1)} \underline{\underline{\det(\lambda I - A_{22})}} \end{aligned}$$

# Upper-Triangularization (Algorithm)

---

**Algorithm 10** Real Schur Decomposition

---

**Input:** A square matrix  $A \in \mathbb{R}^{n \times n}$  with real eigenvalues.

**Output:** An orthonormal matrix  $U \in \mathbb{R}^{n \times n}$  and an upper-triangular matrix  $T \in \mathbb{R}^{n \times n}$  such that  $A = UTU^\top$ .

```
1: function REALSCHURDECOMPOSITION( $A$ )
2:   if  $A$  is  $1 \times 1$  then
3:     return  $\begin{bmatrix} 1 \end{bmatrix}, A$ 
4:   end if
5:    $(\vec{q}_1, \lambda_1) := \text{FINDEIGENVECTOR EIGENVALUE}(A)$ 
6:    $Q := \text{EXTENDBASIS}(\{\vec{q}_1\}, \mathbb{R}^n)$   $\triangleright$  Extend  $\{\vec{q}_1\}$  to a basis of  $\mathbb{R}^n$  using Gram-Schmidt; see Note 13
7:   Unpack  $Q := \begin{bmatrix} \vec{q}_1 & \tilde{Q} \end{bmatrix}$ 
8:   Compute and unpack  $Q^\top A Q = \begin{bmatrix} \lambda_1 & \vec{a}_{12}^\top \\ \vec{0}_{n-1} & \tilde{A}_{22} \end{bmatrix}$ 
9:    $(P, \tilde{T}) := \text{REALSCHURDECOMPOSITION}(\tilde{A}_{22})$ 
10:   $U := \begin{bmatrix} \vec{q}_1 & \tilde{Q}P \end{bmatrix}$ 
11:   $T := \begin{bmatrix} \lambda_1 & \vec{a}_{12}^\top P \\ \vec{0}_{n-1} & \tilde{T} \end{bmatrix}$ 
12:  return  $(U, T)$ 
13: end function
```

---