

Review on 12:00-1:00PM, Friday, Dec. 1

GEPP as LU factorization

Theorem: Let $A = (a_{ij}) \in \mathbf{R}^{n \times n}$ be non-singular. Then GEPP computes an LU factorization with permutation matrix P such that

$$P \cdot A = L \cdot U = \begin{pmatrix} \triangle & \\ & \square \end{pmatrix} \cdot \begin{pmatrix} \triangle & \\ & \square \end{pmatrix}.$$

$P \cdot A = L \cdot U$, Proof by Induction

► GEPP for $n = 2$, $A = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}$.

► **pivoting:**

$$\mathbf{piv}_1 \stackrel{\text{def}}{=} \operatorname{argmax}_{1 \leq j \leq 2} |a_{j1}|, \quad P = \begin{cases} I, & \text{if } \mathbf{piv}_1 = 1, \\ P_{1,2} & \text{if } \mathbf{piv}_1 = 2. \end{cases}$$

► **elimination:**

$$P \cdot A = L \cdot U.$$

$P \cdot A = L \cdot U$, Proof by Induction

► GEPP for $n \geq 3$, $A = \begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{pmatrix} :$

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► **elimination:**

$$\bar{P} \cdot A = \begin{pmatrix} 1 & & & \\ & I_{n-1} & & \end{pmatrix} \cdot \left(\begin{array}{c|ccc} a_{11} & a_{12} & \cdots & a_{1n} \\ \hline 0 & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 0 & a_{n2} & \cdots & a_{nn} \end{array} \right), \quad \left(I \stackrel{\text{def}}{=} \begin{pmatrix} I_{21} \\ \vdots \\ I_{n1} \end{pmatrix} \right)$$

$P \cdot A = L \cdot U$, Proof by Induction

► GEPP for $n \geq 3$, $A = \begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{pmatrix} :$

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► **Induction hypothesis:**

$$\hat{P} \cdot \begin{pmatrix} a_{22} & \cdots & a_{2n} \\ \vdots & \ddots & \vdots \\ a_{n2} & \cdots & a_{nn} \end{pmatrix} = \hat{L} \cdot \hat{U}.$$

► putting it together,

$$\begin{aligned}
 \underbrace{\begin{pmatrix} 1 & \\ & \widehat{\mathbf{P}} \end{pmatrix}}_{\mathbf{P}} \cdot \overline{\mathbf{P}} \cdot \mathbf{A} &= \begin{pmatrix} 1 & \\ & \widehat{\mathbf{P}} \end{pmatrix} \cdot \begin{pmatrix} 1 & \\ & \mathbf{I}_{n-1} \end{pmatrix} \cdot \left(\begin{array}{c|ccc} a_{11} & a_{12} & \cdots & a_{1n} \\ \hline & \mathbf{a}_{22} & \cdots & \mathbf{a}_{2n} \\ & \vdots & \ddots & \vdots \\ & \mathbf{a}_{n2} & \cdots & \mathbf{a}_{nn} \end{array} \right) \\
 &= \begin{pmatrix} 1 & & \\ \hline \widehat{\mathbf{P}} \cdot \mathbf{I} & & \widehat{\mathbf{P}} \end{pmatrix} \cdot \left(\begin{array}{c|ccc} a_{11} & \begin{pmatrix} a_{12} & \cdots & a_{1n} \end{pmatrix} \\ \hline & \begin{pmatrix} \mathbf{a}_{22} & \cdots & \mathbf{a}_{2n} \\ \vdots & \ddots & \vdots \\ \mathbf{a}_{n2} & \cdots & \mathbf{a}_{nn} \end{pmatrix} \end{array} \right) \\
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 \end{aligned}$$

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 &\stackrel{\text{def}}{=} \begin{pmatrix} \triangle & \\ & \end{pmatrix} \cdot \begin{pmatrix} \triangle & \\ & \end{pmatrix} \quad \Bigg| \quad \text{What if } \mathbf{A} \text{ is singular?}
 \end{aligned}$$

Solving general linear equations with GEPP

$$A \mathbf{x} = \mathbf{b}, \quad P \cdot A = L \cdot U$$

- ▶ interchanging components in \mathbf{b}

$$P \cdot (A \mathbf{x}) = (P \cdot \mathbf{b}), \quad (L \cdot U) \mathbf{x} = (P \cdot \mathbf{b}).$$

- ▶ solving for \mathbf{b} with forward and backward substitution

$$\begin{aligned} \mathbf{x} &= (L \cdot U)^{-1} (P \cdot \mathbf{b}) \\ &= (U^{-1} (L^{-1} (P \cdot \mathbf{b}))). \end{aligned}$$

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Cost Analysis

- ▶ computing $P \cdot A = L \cdot U$: about $2/3n^3$ operations.
- ▶ forward and backward substitution: about $2n^2$ operations.
- ▶ most important to compute $P \cdot A = L \cdot U$ **efficiently**

§6.6 Strictly Diagonally Dominant (**SDD**) Matrices

► **Definition:** Matrix $A = (a_{ij}) \in \mathbf{R}^{n \times n}$ is **SDD** if

$$|a_{ii}| > \sum_{j=1, j \neq i}^n |a_{ij}| \quad \text{holds for each } i = 1, 2, \dots, n.$$

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► Example I: matrix $A = \begin{pmatrix} 7 & 2 & 0 \\ 3 & 5 & -1 \\ 0 & 5 & -6 \end{pmatrix}$ is **SDD**.

$$|7| > |2| + |0|, \quad |5| > |3| + |-1|, \quad |-6| > |0| + |5|.$$

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$$|7| > |2| + |0|, \quad |5| > |3| + |-1|, \quad |-6| > |0| + |5|.$$

► Example II: matrix $B = \begin{pmatrix} 7 & 5 & 0 \\ 3 & 5 & -1 \\ 0 & -3 & 3 \end{pmatrix}$ is NOT **SDD**.

$$|3| \leq |0| + |-3|.$$

GE on **SDD**: succeeds without pivoting (I)

- Let $A = (a_{ij}) \in \mathbf{R}^{n \times n}$ be **SDD**, so

$$|a_{11}| > \sum_{j=1, j \neq 1}^n |a_{1j}| \geq 0.$$

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- elimination with $a_{11} \neq 0$:

$$A = \left(\begin{array}{c|ccc} 1 & & & \\ \hline l_{21} & 1 & & \\ \vdots & & \ddots & \\ l_{n1} & & & 1 \end{array} \right) \cdot \left(\begin{array}{c|ccc} a_{11} & a_{12} & \cdots & a_{1n} \\ \hline 0 & \hat{\mathbf{a}}_{22} & \cdots & \hat{\mathbf{a}}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 0 & \hat{\mathbf{a}}_{n2} & \cdots & \hat{\mathbf{a}}_{nn} \end{array} \right),$$

$$l_{j1} = \frac{a_{j1}}{a_{11}}, \quad \hat{\mathbf{a}}_{jk} = a_{jk} - \frac{a_{j1}}{a_{11}} a_{1k}, \quad 2 \leq j \leq n, \quad 2 \leq k \leq n.$$

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- ▶ **only do**: show $\hat{\mathbf{A}} \stackrel{\text{def}}{=} \begin{pmatrix} \hat{a}_{22} & \cdots & \hat{a}_{2n} \\ \vdots & \ddots & \vdots \\ \hat{a}_{n2} & \cdots & \hat{a}_{nn} \end{pmatrix}$ remains **SDD**.

GE on **SDD**: only need to show $\hat{\mathbf{A}}$ remains **SDD**

$$|a_{11}| > \sum_{j=1, j \neq 1}^n |a_{1j}|, \quad |a_{ii}| > \sum_{j=1, j \neq i}^n |a_{ij}|, \quad i = 2, \dots, n,$$

$$\hat{\mathbf{A}} = \begin{pmatrix} \hat{\mathbf{a}}_{22} & \cdots & \hat{\mathbf{a}}_{2n} \\ \vdots & \ddots & \vdots \\ \hat{\mathbf{a}}_{n2} & \cdots & \hat{\mathbf{a}}_{nn} \end{pmatrix}, \quad \hat{\mathbf{a}}_{ij} = a_{ij} - \frac{a_{i1}}{a_{11}} a_{1j}.$$

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► for $i = 2, \dots, n$,

$$\sum_{j=2, j \neq i}^n |\hat{\mathbf{a}}_{ij}| = \sum_{j=2, j \neq i}^n \left| a_{ij} - \frac{a_{i1}}{a_{11}} a_{1j} \right| \leq \left(\sum_{j=2, j \neq i}^n |a_{ij}| \right) + \left| \frac{a_{i1}}{a_{11}} \right| \left(\sum_{j=2, j \neq i}^n |a_{1j}| \right)$$

GE on **SDD**: only need to show $\hat{\mathbf{A}}$ remains **SDD**

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GE on **SDD**: only need to show $\hat{\mathbf{A}}$ remains **SDD**

$$|a_{11}| > \sum_{j=1, j \neq 1}^n |a_{1j}|, \quad |a_{ii}| > \sum_{j=1, j \neq i}^n |a_{ij}|, \quad i = 2, \dots, n,$$

$$\hat{\mathbf{A}} = \begin{pmatrix} \hat{\mathbf{a}}_{22} & \cdots & \hat{\mathbf{a}}_{2n} \\ \vdots & \ddots & \vdots \\ \hat{\mathbf{a}}_{n2} & \cdots & \hat{\mathbf{a}}_{nn} \end{pmatrix}, \quad \hat{\mathbf{a}}_{ij} = a_{ij} - \frac{a_{i1}}{a_{11}} a_{1j}.$$

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GE on **SDD**: example

$$A = \begin{pmatrix} 7 & 2 & 0 \\ 3 & 5 & -1 \\ 0 & 5 & -6 \end{pmatrix} \text{ is } \mathbf{SDD}.$$

$$A = \begin{pmatrix} 1 & & \\ \frac{3}{7} & 1 & \\ 0 & & 1 \end{pmatrix} \cdot \begin{pmatrix} 7 & 2 & 0 \\ \frac{29}{7} & -1 & \\ 5 & -6 & \end{pmatrix} \left[\begin{pmatrix} \frac{29}{7} & -1 \\ 5 & -6 \end{pmatrix} \text{ is } \mathbf{SDD} \right]$$

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Symmetric Positive Definite Matrices

► **Definition:** Matrix $A = (a_{ij}) \in \mathbf{R}^{n \times n}$ is **SPD** if

$$A = A^T, \quad \mathbf{x}^T A \mathbf{x} > 0 \quad \text{for any non-zero } \mathbf{x} \in \mathbf{R}^n.$$

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► **Example I:** matrix

$$\hat{A} = \begin{pmatrix} \boxed{0} & -1 & 0 \\ -1 & 2 & -1 \\ 0 & -1 & 2 \end{pmatrix} = \hat{A}^T$$

IS NOT SPD:

$$\begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}^T \begin{pmatrix} \boxed{0} & -1 & 0 \\ -1 & 2 & -1 \\ 0 & -1 & 2 \end{pmatrix} \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix} = 0$$

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► **Example II:** matrix $A = \begin{pmatrix} \boxed{2} & -1 & 0 \\ -1 & 2 & -1 \\ 0 & -1 & 2 \end{pmatrix} = A^T$

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PROOF: Let $\mathbf{x} = \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} \neq \mathbf{0}$,

↓

$$\mathbf{x}^T A \mathbf{x} = \begin{pmatrix} x_1 & x_2 & x_3 \end{pmatrix} \begin{pmatrix} 2 & -1 & 0 \\ -1 & 2 & -1 \\ 0 & -1 & 2 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix}$$

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$$\begin{aligned} \mathbf{x}^T A \mathbf{x} &= \begin{pmatrix} x_1 & x_2 & x_3 \end{pmatrix} \begin{pmatrix} 2 & -1 & 0 \\ -1 & 2 & -1 \\ 0 & -1 & 2 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} \\ &= \begin{pmatrix} x_1 & x_2 & x_3 \end{pmatrix} \begin{pmatrix} 2x_1 - x_2 \\ -x_1 + 2x_2 - x_3 \\ -x_2 + 2x_3 \end{pmatrix} = 2x_1^2 - 2x_1 x_2 + 2x_2^2 - 2x_2 x_3 + 2x_3^2 \end{aligned}$$

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PROOF: Let $\mathbf{x} = \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} \neq \mathbf{0}$,

↓

$$\begin{aligned} \mathbf{x}^T A \mathbf{x} &= \begin{pmatrix} x_1 & x_2 & x_3 \end{pmatrix} \begin{pmatrix} 2 & -1 & 0 \\ -1 & 2 & -1 \\ 0 & -1 & 2 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} \\ &= \begin{pmatrix} x_1 & x_2 & x_3 \end{pmatrix} \begin{pmatrix} 2x_1 - x_2 \\ -x_1 + 2x_2 - x_3 \\ -x_2 + 2x_3 \end{pmatrix} = 2x_1^2 - 2x_1 x_2 + 2x_2^2 - 2x_2 x_3 + 2x_3^2 \end{aligned}$$

$$\begin{aligned} &\text{rearranging} \quad x_1^2 + (x_1^2 - 2x_1 x_2 + x_2^2) + (x_2^2 - 2x_2 x_3 + x_3^2) + x_3^2 \\ &= x_1^2 + (x_1 - x_2)^2 + (x_2 - x_3)^2 + x_3^2 > 0 \end{aligned}$$

GE on **SPD**: faster and succeeds without pivoting (I)

- Let $A = (a_{ij}) \in \mathbf{R}^{n \times n}$ be **SPD**, then

$$A^T = A, \text{ therefore } a_{jk} = a_{kj} \text{ for all } 1 \leq j, k \leq n$$

$$a_{11} = \begin{pmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{pmatrix}^T \cdot A \cdot \begin{pmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{pmatrix} > 0$$

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- elimination without pivoting

$$A = \begin{pmatrix} 1 & & & \\ l_{21} & 1 & & \\ \vdots & & \ddots & \\ l_{n1} & & & 1 \end{pmatrix} \cdot \left(\begin{array}{c|ccc} a_{11} & a_{12} & \cdots & a_{1n} \\ \hline 0 & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 0 & a_{n2} & \cdots & a_{nn} \end{array} \right)$$

- for $j \geq k = 2, \dots, n$

$$l_{j1} = \frac{a_{j1}}{a_{11}}$$

$$a_{j,k} \leftarrow l_{j1} a_{1k}$$

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$$\text{Define } l_1 \stackrel{\text{def}}{=} \begin{pmatrix} l_{21} \\ \vdots \\ l_{n1} \end{pmatrix}, \quad \hat{A} \stackrel{\text{def}}{=} \begin{pmatrix} a_{22} & \cdots & a_{2n} \\ \vdots & \ddots & \vdots \\ a_{n2} & \cdots & a_{nn} \end{pmatrix} = \hat{A}^T, \text{ then}$$

$$A = \begin{pmatrix} 1 & & \\ l_1 & I \end{pmatrix} \cdot \begin{pmatrix} a_{11} & a_{11} l_1^T \\ & \hat{A} \end{pmatrix} \iff \text{Gaussian elimination}$$

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$$A = \begin{pmatrix} 1 & & \\ \mathbf{l}_1 & \mathbf{I} & \end{pmatrix} \cdot \begin{pmatrix} a_{11} & a_{11} \mathbf{l}_1^T \\ & \hat{\mathbf{A}} \end{pmatrix} \quad \Leftarrow \text{Gaussian elimination}$$

$$= \begin{pmatrix} 1 & & \\ \mathbf{l}_1 & \mathbf{I} & \end{pmatrix} \cdot \begin{pmatrix} a_{11} & \\ & \hat{\mathbf{A}} \end{pmatrix} \begin{pmatrix} 1 & \mathbf{l}_1^T \\ & \mathbf{I} \end{pmatrix} \quad \Leftarrow \text{due to symmetry of } A$$

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next step: show \hat{A} remains **SPD**

$$A = \begin{pmatrix} 1 & \\ \mathbf{l}_1 & \mathbf{I} \end{pmatrix} \cdot \begin{pmatrix} a_{11} & \\ & \hat{\mathbf{A}} \end{pmatrix} \begin{pmatrix} 1 & \\ \mathbf{l}_1 & \mathbf{I} \end{pmatrix}^T$$

- ▶ Let $\hat{\mathbf{x}} \in \mathbf{R}^{n-1}$ be any non-zero vector.
Must show $\hat{\mathbf{x}}^T \cdot \hat{\mathbf{A}} \hat{\mathbf{x}} > 0$ for $\hat{\mathbf{A}}$ to be **SPD**.
- ▶ Note that

$$\mathbf{x} \stackrel{\text{def}}{=} \begin{pmatrix} -\hat{\mathbf{x}}^T \mathbf{l}_1 \\ \hat{\mathbf{x}} \end{pmatrix} \in \mathbf{R}^n \text{ is non-zero} \implies \mathbf{x}^T \cdot A \cdot \mathbf{x} > 0$$

$$\begin{pmatrix} 0 \\ \hat{\mathbf{x}} \end{pmatrix} = \begin{pmatrix} 1 & \\ \mathbf{l}_1 & \mathbf{I} \end{pmatrix}^T \cdot \begin{pmatrix} -\mathbf{l}_1^T \hat{\mathbf{x}} \\ \hat{\mathbf{x}} \end{pmatrix}$$

$$A = \begin{pmatrix} 1 & \\ l_1 & \end{pmatrix} \cdot \begin{pmatrix} a_{11} & \\ & \hat{\mathbf{A}} \end{pmatrix} \begin{pmatrix} 1 & \\ l_1 & \end{pmatrix}^T$$

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- ▶ consequently,

$$\begin{aligned} \hat{\mathbf{x}}^T \cdot \hat{\mathbf{A}} \cdot \hat{\mathbf{x}} &= \begin{pmatrix} 0 \\ \hat{\mathbf{x}} \end{pmatrix}^T \cdot \begin{pmatrix} a_{11} & \\ & \hat{\mathbf{A}} \end{pmatrix} \cdot \begin{pmatrix} 0 \\ \hat{\mathbf{x}} \end{pmatrix} \\ &= \begin{pmatrix} -l_1^T \hat{\mathbf{x}} \\ \hat{\mathbf{x}} \end{pmatrix}^T \cdot \begin{pmatrix} 1 & \\ l_1 & \end{pmatrix} \cdot \begin{pmatrix} a_{11} & \\ & \hat{\mathbf{A}} \end{pmatrix} \begin{pmatrix} 1 & \\ l_1 & \end{pmatrix}^T \cdot \begin{pmatrix} -l_1^T \hat{\mathbf{x}} \\ \hat{\mathbf{x}} \end{pmatrix} \\ &= \mathbf{x}^T \cdot A \cdot \mathbf{x} > 0 \end{aligned}$$

Major Cholesky, 1875 - 1918



- ▶ Invented Cholesky factorization for geodesic work
- ▶ Fell for his country (France) in WWI

Cholesky factorization for SPD matrix: $A = L D L^T$

► Cholesky for $n = 2$:

$$\begin{aligned} A &= \begin{pmatrix} a_{11} & a_{21} \\ a_{21} & a_{22} \end{pmatrix} \quad [A \text{ is symmetric}] \\ &= \begin{pmatrix} 1 & \\ l_{21} & 1 \end{pmatrix} \cdot \begin{pmatrix} a_{11} & \\ & \mathbf{a}_{22} \end{pmatrix} \cdot \begin{pmatrix} 1 & \\ l_{21} & 1 \end{pmatrix}^T, \quad \left[l_{21} = \frac{a_{21}}{a_{11}} \right] \\ &\stackrel{\text{def}}{=} L \cdot D \cdot L^T = \begin{pmatrix} \triangle \\ \square \end{pmatrix} \cdot \begin{pmatrix} \diagdown \\ \diagup \end{pmatrix} \cdot \begin{pmatrix} \triangle \\ \square \end{pmatrix}^T, \end{aligned}$$

Cholesky factorization for SPD matrix: $A = L D L^T$

► Cholesky for $n \geq 3$:

$$A = \begin{pmatrix} a_{11} & a_{21} & \cdots & a_{n1} \\ a_{21} & a_{22} & \cdots & a_{n2} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{pmatrix} \quad [A \text{ is symmetric}]$$
$$= \begin{pmatrix} 1 & & & \\ \mathbf{l} & I_{n-1} & & \end{pmatrix} \cdot \begin{pmatrix} a_{11} & & & \\ & \mathbf{a}_{22} & \cdots & \mathbf{a}_{2n} \\ & \vdots & \ddots & \vdots \\ & \mathbf{a}_{n2} & \cdots & \mathbf{a}_{nn} \end{pmatrix} \cdot \begin{pmatrix} 1 & & & \\ \mathbf{l} & I_{n-1} & & \end{pmatrix}^T,$$

$$\text{where } \mathbf{l} \stackrel{\text{def}}{=} \begin{pmatrix} l_{21} \\ \vdots \\ l_{n1} \end{pmatrix}.$$

Cholesky factorization for SPD matrix: $A = L D L^T$

► induction hypothesis

$$\begin{pmatrix} \mathbf{a}_{22} & \cdots & \mathbf{a}_{2n} \\ \vdots & \ddots & \vdots \\ \mathbf{a}_{n2} & \cdots & \mathbf{a}_{nn} \end{pmatrix} = \hat{\mathbf{L}} \hat{\mathbf{D}} \hat{\mathbf{L}}^T = \begin{pmatrix} \triangle \\ \text{---} \end{pmatrix} \cdot \begin{pmatrix} \diagdown \\ \text{---} \end{pmatrix} \cdot \begin{pmatrix} \triangle \\ \text{---} \end{pmatrix}^T$$

Cholesky factorization for SPD matrix: $A = L D L^T$

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► Cholesky factorization

$$\begin{aligned} A &= \begin{pmatrix} 1 & & \\ \mathbf{I} & I \end{pmatrix} \cdot \begin{pmatrix} a_{11} & & \\ & \begin{pmatrix} \mathbf{a}_{22} & \cdots & \mathbf{a}_{2n} \\ \vdots & \ddots & \vdots \\ \mathbf{a}_{n2} & \cdots & \mathbf{a}_{nn} \end{pmatrix} & \\ & & \end{pmatrix} \cdot \begin{pmatrix} 1 & & \\ \mathbf{I} & I \end{pmatrix}^T, \\ &= \begin{pmatrix} 1 & & \\ \mathbf{I} & I \end{pmatrix} \cdot \begin{pmatrix} a_{11} & & \\ & \hat{\mathbf{L}} \hat{\mathbf{D}} \hat{\mathbf{L}}^T & \\ & & \end{pmatrix} \cdot \begin{pmatrix} 1 & & \\ \mathbf{I} & I \end{pmatrix}^T, \\ &= \begin{pmatrix} 1 & & \\ \mathbf{I} & \hat{\mathbf{L}} \end{pmatrix} \cdot \begin{pmatrix} a_{11} & & \\ & \hat{\mathbf{D}} & \\ & & \end{pmatrix} \cdot \begin{pmatrix} 1 & & \\ \mathbf{I} & \hat{\mathbf{L}} \end{pmatrix}^T = \begin{pmatrix} \triangle \\ \text{---} \end{pmatrix} \cdot \begin{pmatrix} \diagdown \\ \text{---} \end{pmatrix} \cdot \begin{pmatrix} \triangle \\ \text{---} \end{pmatrix}^T. \end{aligned}$$

Cholesky factorization $A = L D L^T$: example

$$A = \begin{pmatrix} 4 & -1 & 1 \\ -1 & 4.25 & 2.75 \\ 1 & 2.75 & 3.5 \end{pmatrix} = A^T.$$

$$A = \begin{pmatrix} 1 & & \\ -\frac{1}{4} & 1 & \\ \frac{1}{4} & & 1 \end{pmatrix} \cdot \begin{pmatrix} 4 & & \\ & 4 & 3 \\ & 3 & \frac{13}{4} \end{pmatrix} \cdot \begin{pmatrix} 1 & & \\ -\frac{1}{4} & 1 & \\ \frac{1}{4} & & 1 \end{pmatrix}^T$$

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Cholesky factorization is a special LU factorization

- ▶ $A = L D L^T = L U$, with $U = D L^T = \begin{pmatrix} \diagup \end{pmatrix}$
- ▶ only L need to be computed, saving half of the work in factorization.
- ▶ total cost: about $\frac{1}{3}n^3$ operations.

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"But Cholesky factorization should not have a $D \dots$ "

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"But Cholesky factorization should not have a $D \dots$ "

$$D = \begin{pmatrix} d_1 & & \\ & \ddots & \\ & & d_n \end{pmatrix} = \left(D^{\frac{1}{2}}\right)^2, \quad \text{for } D^{\frac{1}{2}} \stackrel{\text{def}}{=} \begin{pmatrix} d_1^{\frac{1}{2}} & & \\ & \ddots & \\ & & d_n^{\frac{1}{2}} \end{pmatrix}$$
$$A = L \left(D^{\frac{1}{2}}\right)^2 L^T = \left(L D^{\frac{1}{2}}\right) \left(L D^{\frac{1}{2}}\right)^T = \begin{pmatrix} \triangle & & \\ & \triangle & \\ & & \triangle \end{pmatrix} \cdot \begin{pmatrix} \triangle & & \\ & \triangle & \\ & & \triangle \end{pmatrix}^T$$

Example:

$$A = \begin{pmatrix} 1 & & \\ -\frac{1}{4} & 1 & \\ \frac{1}{4} & \frac{3}{4} & 1 \end{pmatrix} \cdot \begin{pmatrix} 4 & & \\ & 4 & \\ & & 1 \end{pmatrix} \cdot \begin{pmatrix} 1 & & \\ -\frac{1}{4} & 1 & \\ \frac{1}{4} & \frac{3}{4} & 1 \end{pmatrix}^T$$
$$= \begin{pmatrix} 2 & & \\ -\frac{1}{2} & 2 & \\ \frac{1}{2} & \frac{3}{2} & 1 \end{pmatrix} \cdot \begin{pmatrix} 2 & & \\ -\frac{1}{2} & 2 & \\ \frac{1}{2} & \frac{3}{2} & 1 \end{pmatrix}^T$$

Review: Natural Splines equations in matrix form

Equations for spline coefficients $\{c_j\}_{j=1}^{n-1}$,

$$A \cdot \begin{pmatrix} c_1 \\ c_2 \\ \vdots \\ c_{n-2} \\ c_{n-1} \end{pmatrix} = \mathbf{rhs},$$

where

$$A \stackrel{\text{def}}{=} \begin{pmatrix} 2(h_0 + h_1) & h_1 & & & & \\ h_1 & 2(h_1 + h_2) & h_2 & & & \\ & \ddots & \ddots & \ddots & & \\ & & h_{n-3} & 2(h_{n-3} + h_{n-2}) & h_{n-2} & \\ & & & h_{n-2} & 2(h_{n-2} + h_{n-1}) & \end{pmatrix}$$

A is SDD, SPD, and tri-diagonal

DEFINITION: $A \in \mathbf{R}^{n \times n}$ is **tri-diagonal** if

$$A = \begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{pmatrix}$$

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LU should GREATLY simplify since A has so many zero entries

Tri-diagonal LU factorization with $a_{jj} \neq 0$

$$A = \begin{pmatrix} a_{11} & a_{12} & & & \\ a_{21} & a_{22} & a_{23} & & \\ & \ddots & & \ddots & \\ & & a_{n-1,n-2} & a_{n-1,n-1} & a_{n-1,n} \\ & & & a_{n,n-1} & a_{n,n} \end{pmatrix}$$

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$$\begin{aligned}
 A &= \begin{pmatrix} a_{11} & a_{12} & & & \\ a_{21} & a_{22} & a_{23} & & \\ & \ddots & \ddots & \ddots & \\ & & a_{n-1,n-2} & a_{n-1,n-1} & a_{n-1,n} \\ & & & a_{n,n-1} & a_{n,n} \end{pmatrix} \quad \left(\text{set } l_{21} = \frac{a_{21}}{a_{11}} \text{ and } a_{22} = a_{22} - l_{21} a_{12} \right) \\
 &= \begin{pmatrix} 1 & & & & \\ l_{21} & 1 & & & \\ & & \ddots & & \\ & & & 1 & \\ & & & & 1 \end{pmatrix} \cdot \begin{pmatrix} \hline a_{11} & a_{12} & & & \\ \hline a_{22} & a_{23} & & & \\ & \ddots & \ddots & \ddots & \\ & & a_{n-1,n-2} & a_{n-1,n-1} & a_{n-1,n} \\ & & & a_{n,n-1} & a_{n,n} \end{pmatrix}
 \end{aligned}$$

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$$\begin{aligned}
 A &= \begin{pmatrix} a_{11} & a_{12} & & & \\ a_{21} & a_{22} & a_{23} & & \\ & \ddots & \ddots & \ddots & \\ & & a_{n-1,n-2} & a_{n-1,n-1} & a_{n-1,n} \\ & & & a_{n,n-1} & a_{n,n} \end{pmatrix} \quad \left(\text{set } l_{21} = \frac{a_{21}}{a_{11}} \text{ and } a_{22} = a_{22} - l_{21} a_{12} \right) \\
 &= \begin{pmatrix} 1 & & & & \\ l_{21} & 1 & & & \\ & & \ddots & & \\ & & & 1 & \\ & & & & 1 \end{pmatrix} \cdot \begin{pmatrix} \hline a_{11} & a_{12} & & & \\ a_{22} & a_{23} & & & \\ \hline & \ddots & \ddots & \ddots & \\ & & a_{n-1,n-2} & a_{n-1,n-1} & a_{n-1,n} \\ & & & a_{n,n-1} & a_{n,n} \end{pmatrix}
 \end{aligned}$$

► elimination = computing l_{21} and a_{22} (3 operations)

Tri-diagonal LU factorization with $a_{jj} \neq 0$

$$A = \begin{pmatrix} a_{11} & a_{12} & & & \\ a_{21} & a_{22} & a_{23} & & \\ & \ddots & \ddots & \ddots & \\ & & a_{n-1,n-2} & a_{n-1,n-1} & a_{n-1,n} \\ & & & a_{n,n-1} & a_{n,n} \end{pmatrix} \quad \left(\text{set } l_{21} = \frac{a_{21}}{a_{11}} \text{ and } a_{22} = a_{22} - l_{21} a_{12} \right)$$

$$= \begin{pmatrix} 1 & & & & \\ l_{21} & 1 & & & \\ & & \ddots & & \\ & & & 1 & \\ & & & & 1 \end{pmatrix} \cdot \left(\begin{array}{c|ccc} a_{11} & a_{12} & a_{23} & & \\ \hline a_{22} & & & & \\ \ddots & \ddots & \ddots & \ddots & \\ & a_{n-1,n-2} & a_{n-1,n-1} & a_{n-1,n} & \\ & & a_{n,n-1} & a_{n,n} & \end{array} \right)$$

- ▶ elimination = computing l_{21} and a_{22} (3 operations)
- ▶ Trailing matrix remains **tri-diagonal**

Recursively on all trailing matrices,

$$A = \begin{pmatrix} 1 & & & & \\ l_{21} & 1 & & & \\ & \ddots & \ddots & \ddots & \\ & & l_{n-1,n-2} & 1 & \\ & & & l_{n,n-1} & 1 \end{pmatrix} \begin{pmatrix} a_{11} & a_{12} & a_{23} & & \\ & a_{22} & & & \\ & & \ddots & \ddots & \\ & & & a_{n-1,n-1} & a_{n-1,n} \\ & & & & a_{n,n} \end{pmatrix}$$

▶ for $j = 1, \dots, n-1$

$$l_{j+1,j} = \frac{a_{j+1,j}}{a_{jj}}$$

$$a_{j+1,j+1} \leftarrow a_{j+1,j+1} - l_{j+1,j} a_{j,j+1}$$

grand total: $3n$ operations, **if** $a_{jj} \neq 0$ for all j

(non-singular) **tri-diagonal** LU factorization with partial pivoting (I)

- Assume $|a_{11}| \geq |a_{21}|$. Let $l_{21} = \frac{a_{21}}{a_{11}}$ and $\bar{a}_{22} = a_{22} - l_{21} a_{12}$, then

$$A = \left(\begin{array}{c|cccc} 1 & & & & \\ l_{21} & 1 & & & \\ & & \ddots & & \\ & & & 1 & \\ & & & & 1 \end{array} \right) \cdot \left(\begin{array}{c|cccc} a_{11} & a_{12} & & & \\ \hline \bar{a}_{22} & & a_{23} & & \\ & \ddots & & \ddots & \\ & & a_{n-1,n-2} & a_{n-1,n-1} & a_{n-1,n} \\ & & & a_{n,n-1} & a_{n,n} \end{array} \right)$$

elimination only means computing l_{21} and \bar{a}_{22}

(non-singular) **tri-diagonal** LU factorization with partial pivoting (I)

- Assume $|a_{11}| \geq |a_{21}|$. Let $l_{21} = \frac{a_{21}}{a_{11}}$ and $\bar{a}_{22} = a_{22} - l_{21} a_{12}$, then

$$A = \left(\begin{array}{c|cccc} 1 & & & & \\ l_{21} & 1 & & & \\ & & \ddots & & \\ & & & 1 & \\ & & & & 1 \end{array} \right) \cdot \left(\begin{array}{c|cccc} a_{11} & a_{12} & & & \\ \hline \bar{a}_{22} & & a_{23} & & \\ & \ddots & & \ddots & \\ & & a_{n-1,n-2} & a_{n-1,n-1} & a_{n-1,n} \\ & & & a_{n,n-1} & a_{n,n} \end{array} \right)$$

elimination only means computing l_{21} and \bar{a}_{22}

Trailing matrix $\left(\begin{array}{cccc} \bar{a}_{22} & a_{23} & & \\ & \ddots & & \\ & & a_{n-1,n-2} & a_{n-1,n-1} & a_{n-1,n} \\ & & & a_{n,n-1} & a_{n,n} \end{array} \right)$ **tri-diagonal**

(non-singular) **tri-diagonal** LU factorization with partial pivoting (I)

- Assume $|a_{11}| \geq |a_{21}|$. Let $l_{21} = \frac{a_{21}}{a_{11}}$ and $\bar{a}_{22} = a_{22} - l_{21} a_{12}$, then

$$A = \left(\begin{array}{c|cccc} 1 & & & & \\ l_{21} & 1 & & & \\ \hline & & \ddots & & \\ & & & 1 & \\ & & & & 1 \end{array} \right) \cdot \left(\begin{array}{c|cccc} a_{11} & a_{12} & & & \\ \hline \bar{a}_{22} & & a_{23} & & \\ \vdots & \ddots & \ddots & \ddots & \\ & a_{n-1,n-2} & a_{n-1,n-1} & a_{n-1,n} & \\ & & a_{n,n-1} & a_{n,n} & \end{array} \right)$$

elimination only means computing l_{21} and \bar{a}_{22}

Trailing matrix $\left(\begin{array}{cccc} \bar{a}_{22} & a_{23} & & \\ \vdots & \ddots & \ddots & \\ & a_{n-1,n-2} & a_{n-1,n-1} & a_{n-1,n} \\ & & a_{n,n-1} & a_{n,n} \end{array} \right)$ **tri-diagonal**

- Otherwise $|a_{21}| > |a_{11}|$. Let $l_{21} = \frac{a_{11}}{a_{21}}$ and $(\bar{a}_{22}, \bar{a}_{23}) = (a_{12} - l_{21} a_{22}, -l_{21} a_{23})$

$$P_{2,1} \cdot A = \left(\begin{array}{c|cccc} 1 & & & & \\ l_{21} & 1 & & & \\ \hline & & \ddots & & \\ & & & 1 & \\ & & & & 1 \end{array} \right) \cdot \left(\begin{array}{c|cccc} a_{21} & a_{22} & a_{23} & & \\ \hline \bar{a}_{22} & \bar{a}_{23} & & & \\ \vdots & \ddots & \ddots & \ddots & \\ & a_{n-1,n-2} & a_{n-1,n-1} & a_{n-1,n} & \\ & & a_{n,n-1} & a_{n,n} & \end{array} \right)$$

elimination only means computing l_{21} , \bar{a}_{22} and \bar{a}_{23} . Trailing matrix **tri-diagonal**

(non-singular) **tri-diagonal** LU factorization with partial pivoting (I)

- Assume $|a_{11}| \geq |a_{21}|$. Let $l_{21} = \frac{a_{21}}{a_{11}}$ and $\bar{a}_{22} = a_{22} - l_{21} a_{12}$, then

$$A = \left(\begin{array}{c|cccc} 1 & & & & \\ l_{21} & 1 & & & \\ & & \ddots & & \\ & & & 1 & \\ & & & & 1 \end{array} \right) \cdot \left(\begin{array}{c|cccc} a_{11} & a_{12} & & & \\ \hline \bar{a}_{22} & & a_{23} & & \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ & a_{n-1,n-2} & a_{n-1,n-1} & a_{n-1,n} & \\ & & a_{n,n-1} & a_{n,n} & \end{array} \right)$$

elimination only means computing l_{21} and \bar{a}_{22}

Trailing matrix $\left(\begin{array}{cccc} \bar{a}_{22} & a_{23} & & \\ \vdots & \ddots & \ddots & \\ & a_{n-1,n-2} & a_{n-1,n-1} & a_{n-1,n} \\ & & a_{n,n-1} & a_{n,n} \end{array} \right)$ **tri-diagonal**

- Otherwise $|a_{21}| > |a_{11}|$. Let $l_{21} = \frac{a_{11}}{a_{21}}$ and $(\bar{a}_{22}, \bar{a}_{23}) = (a_{12} - l_{21} a_{22}, -l_{21} a_{23})$

$$P_{2,1} \cdot A = \left(\begin{array}{c|cccc} 1 & & & & \\ l_{21} & 1 & & & \\ & & \ddots & & \\ & & & 1 & \\ & & & & 1 \end{array} \right) \cdot \left(\begin{array}{c|cccc} a_{21} & a_{22} & a_{23} & & \\ \hline \bar{a}_{22} & \bar{a}_{23} & & & \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ & a_{n-1,n-2} & a_{n-1,n-1} & a_{n-1,n} & \\ & & a_{n,n-1} & a_{n,n} & \end{array} \right)$$

elimination only means computing l_{21} , \bar{a}_{22} and \bar{a}_{23} . Trailing matrix **tri-diagonal**

tri-diagonal LU factorization with partial pivoting (II)

Recap: $A = \left(\begin{array}{c|cccc} a_{11} & a_{12} & & & \\ a_{21} & a_{22} & a_{23} & & \\ & \ddots & \ddots & \ddots & \\ & & a_{n-1,n-2} & a_{n-1,n-1} & a_{n-1,n} \\ & & & a_{n,n-1} & a_{n,n} \end{array} \right)$

tri-diagonal LU factorization with partial pivoting (II)

$$\text{Recap: } A = \left(\begin{array}{c|cccc} a_{11} & a_{12} & & & \\ a_{21} & a_{22} & a_{23} & & \\ & \ddots & \ddots & \ddots & \\ & & a_{n-1,n-2} & a_{n-1,n-1} & a_{n-1,n} \\ & & & a_{n,n-1} & a_{n,n} \end{array} \right)$$

$$\mathbf{P}_1 \cdot A = \left(\begin{array}{c|cccc} 1 & & & & \\ \hline l_{21} & 1 & & & \\ & & \ddots & & \\ & & & 1 & \\ & & & & 1 \end{array} \right) \cdot \left(\begin{array}{c|cccc} a_{11} & a_{12} & a_{13} & & \\ \hline a_{22} & a_{23} & & & \\ & \ddots & \ddots & \ddots & \\ & & a_{n-1,n-2} & a_{n-1,n-1} & a_{n-1,n} \\ & & & a_{n,n-1} & a_{n,n} \end{array} \right)$$

cost: at most 4 operations per elimination step, with or without pivoting

$$\text{Recursively: } \hat{\mathbf{P}} \cdot \begin{pmatrix} a_{22} & a_{23} & & \\ \ddots & \ddots & \ddots & \\ & a_{n-1,n-2} & a_{n-1,n-1} & a_{n-1,n} \\ & & a_{n,n-1} & a_{n,n} \end{pmatrix} = \hat{\mathbf{L}} \cdot \hat{\mathbf{U}}$$

- ▶ $\hat{\mathbf{U}}$: upper triangular with bandwidth at most 3.
- ▶ $\hat{\mathbf{L}}$: unit lower triangular with one non-zero in each column below diagonal.

tri-diagonal LU factorization with partial pivoting (III)

$$\text{Together: } \mathbf{P}_1 \cdot A = \left(\begin{array}{c|cccc} 1 & & & & \\ \hline l_{21} & 1 & & & \\ & & \ddots & & \\ & & & 1 & \\ & & & & 1 \end{array} \right) \cdot \left(\begin{array}{c|cccc} \mathbf{a}_{11} & & (\mathbf{a}_{12} \ \mathbf{a}_{13} \) & & \\ \hline & \mathbf{a}_{22} & \mathbf{a}_{23} & & \\ & \ddots & \ddots & \ddots & \\ & & \mathbf{a}_{n-1,n-2} & \mathbf{a}_{n-1,n-1} & \mathbf{a}_{n-1,n} \\ & & & \mathbf{a}_{n,n-1} & \mathbf{a}_{n,n} \end{array} \right)$$

$$\underbrace{\left(\left(\begin{array}{c|c} 1 & \\ \hline & \hat{\mathbf{P}} \end{array} \right) \cdot \mathbf{P}_1 \right)}_P \cdot A = \left(\begin{array}{c|c} 1 & \\ \hline \mathbf{l}_1 & I \end{array} \right) \cdot \left(\begin{array}{c|c} \mathbf{a}_{11} & (\mathbf{a}_{12} \ \mathbf{a}_{13} \) \\ \hline & \hat{\mathbf{L}} \cdot \hat{\mathbf{U}} \end{array} \right), \quad \left(\mathbf{l}_1 = \hat{\mathbf{P}} \left(\begin{array}{c} l_{21} \\ \vdots \\ l_{n1} \end{array} \right) \right)$$

$$= \left(\begin{array}{c|c} 1 & \\ \hline \mathbf{l}_1 & \hat{\mathbf{L}} \end{array} \right) \cdot \left(\begin{array}{c|c} \mathbf{a}_{11} & (\mathbf{a}_{12} \ \mathbf{a}_{13} \) \\ \hline & \hat{\mathbf{U}} \end{array} \right) \stackrel{\text{def}}{=} L \cdot U$$

total cost: at most $4n$ operations and n comparisons

And that is it.



Final Exam, Fri. Dec. 15, 11:30 am - 2:30 pm, Li Ka Shing 245

- ▶ Covers every section in Chapters 1-6, excluding
 - ▶ FALSE POSITION METHOD IN SECTION 2.3,
 - ▶ SECTION 5.8,
 - ▶ SCALED PARTIAL OR COMPLETE PIVOTING IN SECTION 6.2.

Final Exam, Fri. Dec. 15, 11:30 am - 2:30 pm, Li Ka Shing 245

- ▶ Covers every section in Chapters 1-6, excluding
 - ▶ FALSE POSITION METHOD IN SECTION 2.3,
 - ▶ SECTION 5.8,
 - ▶ SCALED PARTIAL OR COMPLETE PIVOTING IN SECTION 6.2.
- ▶ One question each for Chs. 2-3; two each for Chs. 4-6.

Final Exam, Fri. Dec. 15, 11:30 am - 2:30 pm, Li Ka Shing 245

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- ▶ Problems mostly from, or are similar to those in the textbook.

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- ▶ No need to simplify answers unless told to.

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- ▶ Problems mostly from, or are similar to those in the textbook.
- ▶ No need to simplify answers unless told to.
- ▶ Sample exams will be posted.

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- ▶ No need to simplify answers unless told to.
- ▶ Sample exams will be posted.
- ▶ Honor DSP requests.

Final Exam, Fri. Dec. 15, 11:30 am - 2:30 pm, Li Ka Shing 245

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- ▶ One question each for Chs. 2-3; two each for Chs. 4-6.
- ▶ Problems mostly from, or are similar to those in the textbook.
- ▶ No need to simplify answers unless told to.
- ▶ Sample exams will be posted.
- ▶ Honor DSP requests.
- ▶ Cheat sheet: one side on one page

Final Exam, Fri. Dec. 15, 11:30 am - 2:30 pm, Li Ka Shing 245

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- ▶ No need to simplify answers unless told to.
- ▶ Sample exams will be posted.
- ▶ Honor DSP requests.
- ▶ Cheat sheet: one side on one page
- ▶ OH: MW 1:30-3:00PM in 861 Evans or by appointment.

Ch. 2: Question

Let $f(x) = x^2 - a$ for $a > 0$

Apply Secant method to solve the equation $f(x) = 0$ with initial guesses $x_0 > x_1 > \sqrt{a}$:

$$x_{k+1} = x_k - \frac{f(x_k) (x_k - x_{k-1})}{f(x_k) - f(x_{k-1})}, \quad \text{for } k = 1, 2, \dots$$

Ch. 2: Question

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Ch. 2: Question

$$\text{Let } f(x) = x^2 - a \text{ for } a > 0$$

Apply Secant method to solve the equation $f(x) = 0$ with initial guesses $x_0 > x_1 > \sqrt{a}$:

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SOLUTION: Since $x_0 > x_1 > \sqrt{a} > 0$, the denominator for $k = 1$

$$f(x_k) - f(x_{k-1}) = x_k^2 - x_{k-1}^2 = (x_k - x_{k-1}) (x_k + x_{k-1}) \neq 0$$

thus x_2 is defined. In general, for $k \geq 1$,

$$x_{k+1} = x_k - \frac{(x_k^2 - a) (x_k - x_{k-1})}{(x_k - x_{k-1}) (x_k + x_{k-1})} = x_k - \frac{(x_k^2 - a)}{x_k + x_{k-1}} = \frac{x_k x_{k-1} + a}{x_k + x_{k-1}}$$

$$\text{It follows that } x_{k+1} - \sqrt{a} = \frac{x_k x_{k-1} + a - \sqrt{a} (x_k + x_{k-1})}{x_k + x_{k-1}} = \frac{(x_k - \sqrt{a}) (x_{k-1} - \sqrt{a})}{x_k + x_{k-1}} > 0 \quad (1)$$

To show Secant iteration is defined, we must show $x_{k+1} \neq x_k$ for all k . However, if $x_{k+1} = x_k$ for some k , then

$$x_k = \frac{x_k x_{k-1} + a}{x_k + x_{k-1}}, \quad \text{then}$$

Ch. 2: Question

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$$x_k = \frac{x_k x_{k-1} + a}{x_k + x_{k-1}}, \quad \text{then } x_k (x_k + x_{k-1}) = x_k x_{k-1} + a \implies x_k^2 = a$$

Ch. 2: Question

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SOLUTION: Since $x_0 > x_1 > \sqrt{a} > 0$, the denominator for $k = 1$

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$$x_k = \frac{x_k x_{k-1} + a}{x_k + x_{k-1}}, \quad \text{then } x_k (x_k + x_{k-1}) = x_k x_{k-1} + a \implies x_k^2 = a \quad \boxed{\Rightarrow \Leftarrow}$$

Ch. 2: Question

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$$\text{It follows that } x_{k+1} - \sqrt{a} = \frac{x_k x_{k-1} + a - \sqrt{a} (x_k + x_{k-1})}{x_k + x_{k-1}} = \frac{(x_k - \sqrt{a}) (x_{k-1} - \sqrt{a})}{x_k + x_{k-1}} > 0 \quad (1)$$

To show Secant iteration is defined, we must show $x_{k+1} \neq x_k$ for all k . However, if $x_{k+1} = x_k$ for some k , then

$$x_k = \frac{x_k x_{k-1} + a}{x_k + x_{k-1}}, \quad \text{then } x_k (x_k + x_{k-1}) = x_k x_{k-1} + a \implies x_k^2 = a \quad \boxed{\Rightarrow \Leftarrow}$$

From (1), $x_k > \sqrt{a}$ for all k , and therefore (1) implies for all k , $0 < x_{k+1} - \sqrt{a} < x_k - \sqrt{a}$

Ch. 2: Question

Let $f(x) = x^2 - a$ for $a > 0$

Apply Secant method to solve the equation $f(x) = 0$ with initial guesses $x_0 > x_1 > \sqrt{a}$:

$$x_{k+1} = x_k - \frac{f(x_k)(x_k - x_{k-1})}{f(x_k) - f(x_{k-1})}, \quad \text{for } k = 1, 2, \dots. \quad \text{Show that the iteration always converges}$$

SOLUTION: Since $x_0 > x_1 > \sqrt{a} > 0$, the denominator for $k = 1$

$$f(x_k) - f(x_{k-1}) = x_k^2 - x_{k-1}^2 = (x_k - x_{k-1})(x_k + x_{k-1}) \neq 0$$

thus x_2 is defined. In general, for $k \geq 1$,

$$x_{k+1} = x_k - \frac{(x_k^2 - a)(x_k - x_{k-1})}{(x_k - x_{k-1})(x_k + x_{k-1})} = x_k - \frac{(x_k^2 - a)}{x_k + x_{k-1}} = \frac{x_k x_{k-1} + a}{x_k + x_{k-1}}$$

$$\text{It follows that } x_{k+1} - \sqrt{a} = \frac{x_k x_{k-1} + a - \sqrt{a}(x_k + x_{k-1})}{x_k + x_{k-1}} = \frac{(x_k - \sqrt{a})(x_{k-1} - \sqrt{a})}{x_k + x_{k-1}} > 0 \quad (1)$$

To show Secant iteration is defined, we must show $x_{k+1} \neq x_k$ for all k . However, if $x_{k+1} = x_k$ for some k , then

$$x_k = \frac{x_k x_{k-1} + a}{x_k + x_{k-1}}, \quad \text{then } x_k (x_k + x_{k-1}) = x_k x_{k-1} + a \implies x_k^2 = a \quad \boxed{\Rightarrow \Leftarrow}$$

From (1), $x_k > \sqrt{a}$ for all k , and therefore (1) implies for all k , $0 < x_{k+1} - \sqrt{a} < x_k - \sqrt{a}$

Therefore the sequence $\{x_k\}_{k=0}^{\infty}$ monotonically decreases with a lower bound. It must converge.

Ch. 3: Question

Let polynomial

$$P_n(x) \stackrel{\text{def}}{=} a_0 + a_1(x - x_0) + a_2(x - x_0)^2 + \cdots + a_{n+1}(x - x_0)^2(x - x_1) \cdots (x - x_{n-1}) \quad (1)$$

interpolate function $f(x)$ at distinct points x_0, x_1, \dots, x_n such that

$$P_n(x_j) = f(x_j), \quad j = 0, 1, \dots, n \quad \text{and that} \quad P'_n(x_0) = f'(x_0). \quad \textbf{Show that} \quad a_2 = f[x_0, x_0, x_1].$$

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interpolate function $f(x)$ at distinct points x_0, x_1, \dots, x_n such that

$$P_n(x_j) = f(x_j), \quad j = 0, 1, \dots, n \quad \text{and that } P'_n(x_0) = f'(x_0). \quad \text{Show that } a_2 = f[x_0, x_0, x_1].$$

SOLUTION: Let $x = x_0$ in equation (1) to reach $a_0 = P_n(x_0) = f(x_0)$. Additionally,

$$\frac{P_n(x) - f(x_0)}{x - x_0} = a_1 + a_2(x - x_0) + \cdots + a_{n+1}(x - x_0)(x - x_1) \cdots (x - x_{n-1})$$

Let $x \rightarrow x_0$ gives $a_1 = P'_n(x_0) = f'(x_0)$. Now let $x = x_1$, we get

$$f[x_0, x_1] = f[x_0, x_0] + a_2(x_1 - x_0)$$

which implies

$$a_2 = f[x_0, x_0, x_1].$$

Ch. 4: Question

Let $0 < \alpha_1 < \alpha_2 < 1$, and let $N(h)$ be an approximation to a value M for every $h > 0$ such that

$$M = N(h) + k_1 h + k_2 h^2 + k_3 h^3 + \cdots .$$

Find μ_1 and μ_2 such that the expression $\frac{N(h)+\mu_1 N(\alpha_1 h)+\mu_2 N(\alpha_2 h)}{1+\mu_1+\mu_2}$ is an $O(h^3)$ approximation to M .

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Find μ_1 and μ_2 such that the expression $\frac{N(h) + \mu_1 N(\alpha_1 h) + \mu_2 N(\alpha_2 h)}{1 + \mu_1 + \mu_2}$ is an $O(h^3)$ approximation to M .

SOLUTION: We write

$$M = N(h) + k_1 h + k_2 h^2 + k_3 h^3 + \dots$$

$$M = N(\alpha_1 h) + k_1 (\alpha_1 h) + k_2 (\alpha_1 h)^2 + k_3 (\alpha_1 h)^3 + \dots$$

$$M = N(\alpha_2 h) + k_1 (\alpha_2 h) + k_2 (\alpha_2 h)^2 + k_3 (\alpha_2 h)^3 + \dots$$

$$\begin{aligned} \text{It follows that } M &= \frac{N(h) + \mu_1 N(\alpha_1 h) + \mu_2 N(\alpha_2 h)}{1 + \mu_1 + \mu_2} \\ &\quad + \frac{1 + \mu_1 \alpha_1 + \mu_2 \alpha_2}{1 + \mu_1 + \mu_2} k_1 h + \frac{1 + \mu_1 \alpha_1^2 + \mu_2 \alpha_2^2}{1 + \mu_1 + \mu_2} k_2 h^2 + O(h^3) \end{aligned}$$

Thus, we must choose μ_1 and μ_2 such that

$$1 + \mu_1 \alpha_1 + \mu_2 \alpha_2 = 0, \quad 1 + \mu_1 \alpha_1^2 + \mu_2 \alpha_2^2 = 0$$

$$\text{which leads to } \begin{pmatrix} \mu_1 \\ \mu_2 \end{pmatrix} = - \begin{pmatrix} \alpha_1 & \alpha_2 \\ \alpha_1^2 & \alpha_2^2 \end{pmatrix}^{-1} \begin{pmatrix} 1 \\ 1 \end{pmatrix}$$

Ch. 5: Question

Consider an initial value ODE

$$y' = f(t, y), \quad y(t_0) = Y_0, \quad (1)$$

and a method for solving (1)

$$w_{j+1} = w_j + h \left(\alpha f(t_{j+1}, w_{j+1}) + \beta f(t_j, w_j) + \gamma f(t_{j-1}, w_{j-1}) \right), \quad (2)$$

for $j = 0, 1, 2, \dots$.

Find relations on coefficients α, β, γ so that (2) is a second-order method for solving (1).

Ch. 5: Question

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for $j = 0, 1, 2, \dots$.

Find relations on coefficients α, β, γ so that (2) is a second-order method for solving (1).

SOLUTION: By definition, $y'(t_j) = f(t_j, y(t_j))$, $y''(t_j) = \frac{\partial f}{\partial t} + \frac{\partial f}{\partial y} f$

$$\begin{aligned} \text{LTE} &= \frac{y(t_{j+1}) - y(t_j)}{h} - (\alpha f(t_{j+1}, y(t_{j+1})) + \beta f(t_j, y(t_j)) + \gamma f(t_{j-1}, y(t_{j-1}))) \\ &= y'(t_j) + \frac{h}{2} y''(t_j) - (\alpha + \beta + \gamma) f(t_j, y(t_j)) - \left(\alpha h \left(\frac{\partial f}{\partial t} + \frac{\partial f}{\partial y} f \right) - \gamma h \left(\frac{\partial f}{\partial t} + \frac{\partial f}{\partial y} f \right) \right) + O(h^2) \end{aligned}$$

Thus the relations are

$$\alpha + \beta + \gamma = 1, \quad \alpha - \gamma = \frac{1}{2}$$

Ch. 6: Question

Let $h_j > 0$ for $j = 0, 1, \dots, n$, and let

$$A \stackrel{\text{def}}{=} \begin{pmatrix} 2(h_0 + h_1) & h_1 & & & \\ h_1 & 2(h_1 + h_2) & h_2 & & \\ & \ddots & \ddots & \ddots & \\ & & h_{n-2} & 2(h_{n-2} + h_{n-1}) & h_{n-1} \\ & & & h_{n-1} & 2(h_{n-1} + h_n) \end{pmatrix}.$$

Show that A is symmetric positive definite.

Ch. 6: Question

Let $h_j > 0$ for $j = 0, 1, \dots, n$, and let

$$A \stackrel{\text{def}}{=} \begin{pmatrix} 2(h_0 + h_1) & h_1 & & & & \\ h_1 & 2(h_1 + h_2) & h_2 & & & \\ & \ddots & \ddots & \ddots & & \\ & & h_{n-2} & 2(h_{n-2} + h_{n-1}) & h_{n-1} & \\ & & & h_{n-1} & 2(h_{n-1} + h_n) \end{pmatrix}.$$

Show that A is symmetric positive definite.

SOLUTION: A is symmetric. Let $\mathbf{x} = \begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix}$ non-zero. Then

$$\begin{aligned} \mathbf{x}^T A \mathbf{x} &= 2 \left(\sum_{j=1}^n x_j^2 (h_j + h_{j-1}) \right) + 2 \left(\sum_{j=2}^n x_j x_{j-1} h_{j-1} \right) \\ &= 2 \left(\sum_{j=1}^n x_j^2 (h_j + h_{j-1}) \right) + \left(\sum_{j=2}^n ((x_j + x_{j-1})^2 - x_j^2 - x_{j-1}^2) h_{j-1} \right) \\ &= \left(\sum_{j=1}^n x_j^2 (h_j + h_{j-1}) \right) + x_n^2 h_n + x_1^2 h_0 + \left(\sum_{j=2}^n (x_j + x_{j-1})^2 h_{j-1} \right) \\ &> 0 \end{aligned}$$