The Cholesky Factorization and Pivoting Methods in Gaussian Elimination

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MTH 499-02

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Outline

• Cholesky factorization: overview, algorithm, example

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- Pivoting methods in Gaussian Elimination: connections to factorizations, types, example

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- $A = L^*(L^*)^T$, where $L^* = LD^{1/2}$

Unicity: straightforward (assume two, show same)



Cholesky Algorithm

- 1: **function** Cholesky $(n,(a_{ij}))$
- 2: for k = 1 to n do

3:
$$l_{kk} \leftarrow \left(a_{kk} - \sum_{s=1}^{k-1} l_{ks}^2\right)^{1/2}$$

4: **for** i = k + 1 **to** n **do**

5:
$$l_{ik} \leftarrow \left(a_{ik} - \sum_{s=1}^{k-1} l_{is} l_{ks}\right) / l_{kk}$$

6: **return** (l_{ij})

where

- $A = (a_{ij})$: factored matrix
- n: order of A
- $L = (l_{ij})$: resulting lower triangular matrix

$$A = \begin{bmatrix} 25 & 15 & -5 \\ 15 & 18 & 0 \\ -5 & 0 & 11 \end{bmatrix}$$

$$L = \left[\begin{array}{cc} & 0 & 0 \\ & & 0 \end{array} \right]$$

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$$A = \begin{bmatrix} 25 & 15 & -5 \\ 15 & 18 & 0 \\ -5 & 0 & 11 \end{bmatrix}$$

$$L = \begin{bmatrix} 5 & 0 & 0 \\ & & 0 \end{bmatrix}$$

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6: **return**
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$$k = 1$$
:

$$l_{11} = (25 - 0)^{1/2} = 5$$

$$A = \begin{bmatrix} 25 & 15 & -5 \\ 15 & 18 & 0 \\ -5 & 0 & 11 \end{bmatrix}$$

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$$k = 1, \quad i = 2:$$

$$l_{21} = (15 - 0)/5 = 3$$



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$$k = 1, \quad i = 3:$$

$$l_{31} = (-5 - 0)/5 = -1$$



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$$l_{32} = (0 - (-1)(3))/3 = 1$$



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$$k=3$$
:

$$l_{33} = (11 - (-1)^2 - (-1)^2) = 3$$

• Verify correctness:

$$L = \begin{bmatrix} 5 & 0 & 0 \\ 3 & 3 & 0 \\ -1 & 1 & 3 \end{bmatrix}$$

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$$L = \begin{bmatrix} 5 & 0 & 0 \\ 3 & 3 & 0 \\ -1 & 1 & 3 \end{bmatrix} \implies L^T = \begin{bmatrix} 5 & 3 & -1 \\ 0 & 3 & 1 \\ 0 & 0 & 3 \end{bmatrix}$$

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$$L = \begin{bmatrix} 5 & 0 & 0 \\ 3 & 3 & 0 \\ -1 & 1 & 3 \end{bmatrix} \implies L^T = \begin{bmatrix} 5 & 3 & -1 \\ 0 & 3 & 1 \\ 0 & 0 & 3 \end{bmatrix}$$

$$LL^T = \begin{bmatrix} 5 & 0 & 0 \\ 3 & 3 & 0 \\ -1 & 1 & 3 \end{bmatrix} \begin{bmatrix} 5 & 3 & -1 \\ 0 & 3 & 1 \\ 0 & 0 & 3 \end{bmatrix} = \begin{bmatrix} 25 & 15 & -5 \\ 15 & 18 & 0 \\ -5 & 0 & 11 \end{bmatrix} = A$$

Gaussian Elimination

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- Possible row operations:
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- Process which attempts to solve a linear system by reducing the coefficient matrix to triangular form using elementary row operations (the result can then by easily solved using forward/backward substitution)
- Possible row operations:
 - Interchange
 - Scaling
 - Addition
- Gaussian elimination only utilizes scaling and addition!

Gaussian Elimination Algorithm

```
1: function GE(n, (a_{ij}))

2: for k = 1 to n - 1 do

3: for i = k + 1 to n do

4: z \leftarrow a_{ik}/a_{kk}

5: a_{ik} \leftarrow 0

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 - \bullet Example: scale row 2 of $A \in \mathbb{R}^{3 \times 3}$ by 4

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- Define $U = A_{s+1}$ and observe that

$$U = E_s \cdots E_1 A$$
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$$U = E_s \cdots E_1 A$$
 or $A = E_1^{-1} \cdots E_s^{-1} U = LU$

 So, Gaussian elimination constructs an LU factorization (and hence is functionally equivalent to the LU factorization algorithm!)



Pivoting Methods

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 - Unscaled: compare absolute value of entries directly
 - Scaled: compare ratios of pivot entries to maximum entries in magnitude in each row

Pivoting Algorithms

```
1: function GE_PP(n, (a_{ij}), (p_i))
2: for k = 1 to n - 1 do
3: for i = k + 1 to n do
4: z \leftarrow a_{p_i k}/a_{p_k k}
5: a_{p_i k} \leftarrow 0
6: for j = k + 1 to n do
7: a_{p_i j} \leftarrow a_{p_i j} - z a_{p_k j}
8: return (a_{ij})
```

$$A_1 = \begin{bmatrix} 1 & 3 & 6 \\ 2 & 1 & 1 \\ 1 & 3 & 3 \end{bmatrix}$$

$$p = \begin{bmatrix} 1, & 2, & 3 \end{bmatrix}$$

1: function
$$GE_PP(n, (a_{ij}), (p_i))$$

2: **for**
$$k = 1$$
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7:
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8: **return**
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$$\max(\left|1\right|,\left|2\right|,\left|1\right|)=2$$



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$$\max(|1|, |2|, |1|) = 2$$

$$R_1 \leftarrow R_1 - \frac{1}{2}R_2$$

$$R_3 \leftarrow R_3 - \frac{1}{2}R_2$$

$$R_2 \leftarrow \frac{1}{2}R_2$$

$$A_2 = \begin{bmatrix} 0 & 2.5 & 5.5 \\ 1 & 0.5 & 0.5 \\ 0 & 2.5 & 2.5 \end{bmatrix}$$

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$$\max(\left|2.5\right|,\left|2.5\right|)=2.5$$

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$$A_3 = \begin{bmatrix} 0 & 1 & 2.2 \\ 1 & 0.5 & -0.6 \\ 0 & 0 & -3 \end{bmatrix}$$

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8: **return**
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$$R_3 \leftarrow -\frac{1}{3}R_3$$



$$A_4 = \begin{bmatrix} 0 & 1 & 2.2 \\ 1 & 0.5 & -0.6 \\ 0 & 0 & 1 \end{bmatrix}$$
$$p = \begin{bmatrix} 2, & 1, & 3 \end{bmatrix}$$

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