

Idea: error analysis \equiv matrix equation

- ▶ $LU = A \Rightarrow \tilde{L}\tilde{U} = A + \Delta A$;
 ΔA unknown, "error variable".
Error analysis \equiv computing ΔA .
- ▶ $|\Delta A| \leq O(n)\mathbf{u}|\tilde{L}||\tilde{U}|$,
 $|\Delta A| \leq O(n)\mathbf{u}(|\tilde{L}||\tilde{U}| + |A|)$?

$\left\{ \begin{array}{l} \tilde{L}_{00}\tilde{U}_{00} = A_{00} + \Delta A_{00} \quad \tilde{L}_{00}\tilde{u}_{01} = a_{01} + \delta a_{01} \quad \tilde{L}_{00}\tilde{U}_{02} = A_{02} + \Delta A_{02} \\ \tilde{L}_{10}\tilde{U}_{00} = a_{10}^T + \delta a_{10}^T \quad \text{---} \quad \text{---} \\ \tilde{L}_{20}\tilde{U}_{00} = A_{20} + \Delta A_{02} \quad \text{---} \quad \text{---} \end{array} \right\}$		
$v_{11} := \alpha_{11} - l_{10}^T u_{01}$	DOT(1)	Error Updates
$u_{12}^T := a_{12}^T - l_{10}^T U_{02}$	GEMV(1)	
$l_{21} := (a_{21} - L_{20}u_{01})/v_{11}$	GEMV(2)	
$\left\{ \begin{array}{l} \tilde{L}_{00}\tilde{U}_{00} = A_{00} + \Delta A_{00} \quad \tilde{L}_{00}\tilde{u}_{01} = a_{01} + \delta a_{01} \quad \tilde{L}_{00}\tilde{U}_{02} = A_{02} + \Delta A_{02} \\ \tilde{L}_{10}\tilde{U}_{00} = a_{10}^T + \delta a_{10}^T \quad \tilde{L}_{10}\tilde{u}_{01} + \tilde{v}_{11} = \alpha_{11} + \delta \alpha_{11} \quad \tilde{L}_{10}\tilde{U}_{02} + u_{12}^T = a_{12}^T + \delta a_{12}^T \\ \tilde{L}_{20}\tilde{U}_{00} = A_{20} + \Delta A_{20} \quad \tilde{L}_{20}\tilde{u}_{01} + l_{21}\tilde{v}_{11} = a_{21} + \delta a_{21} \quad \text{---} \end{array} \right\}$		

• **Step #1:** From algorithm to loop invariant.

Algorithm: LU

Partition $A \rightarrow \left(\begin{array}{c|c} A_{TL} & A_{TR} \\ \hline A_{BL} & A_{BR} \end{array} \right)$
where A_{TL} is 0×0

While $size(A_{TL}) < size(A)$ **do**

Repartition

$$\left(\begin{array}{c|c} A_{TL} & A_{TR} \\ \hline A_{BL} & A_{BR} \end{array} \right) \rightarrow \left(\begin{array}{c|c|c} A_{00} & a_{01} & A_{02} \\ \hline a_{10}^T & \alpha_{11} & a_{12}^T \\ \hline A_{20} & a_{21} & A_{22} \end{array} \right)$$

$$\alpha_{11} := \alpha_{11} - a_{10}^T a_{01} \quad \text{DOT}(1)$$

$$a_{12}^T := (a_{12}^T - a_{10}^T A_{02}) \quad \text{GEMV}(1)$$

$$a_{21} := (a_{21} - A_{20} a_{01}) / \alpha_{11} \quad \text{GEMV}(2)$$

Continue

$$\left(\begin{array}{c|c} A_{TL} & A_{TR} \\ \hline A_{BL} & A_{BR} \end{array} \right) \leftarrow \left(\begin{array}{c|c|c} A_{00} & a_{01} & A_{02} \\ \hline a_{10}^T & \alpha_{11} & a_{12}^T \\ \hline A_{20} & a_{21} & A_{22} \end{array} \right)$$

endwhile

Algorithm Progression

DONE	DONE	DONE
DONE	DOT	GEMV
DONE	GEMV SCAL	

Loop Invariant

$$\left(\begin{array}{c|c} L_{TL}U_{TL} = A_{TL} & L_{TL}U_{TR} = A_{TR} \\ \hline L_{BL}U_{TL} = A_{BL} & \text{---} \end{array} \right)$$

• **Step #2:** From loop invariant to error invariant.

Error Invariant: $\left(\begin{array}{c|c} \tilde{L}_{TL}\tilde{U}_{TL} = A_{TL} + \Delta A_{TL} & \tilde{L}_{TL}\tilde{U}_{TR} = A_{TR} + \Delta A_{TR} \\ \hline \tilde{L}_{BL}\tilde{U}_{TL} = A_{BL} + \Delta A_{BL} & \text{---} \end{array} \right)$

• **Step #3:** From error invariant to subgoals.

The error invariant is expressed in terms of the repartitioned operands.

• **Step #4:** Inventory of known results or new analysis.

Can the error generated at each iteration be accumulated into the error variables ($\delta\alpha_{11}$, δa_{01} , and δa_{12}^T) so that the error invariant remains satisfied?

Subgoals

- ▶ DOT: $v_{11} := \alpha_{11} - l_{10}^T u_{01} \stackrel{?}{\Rightarrow} \tilde{L}_{10}\tilde{u}_{01} + \tilde{v}_{11} = \alpha_{11} + \delta\alpha_{11}$
- ▶ GEMV: $u_{12}^T := a_{12}^T - l_{10}^T U_{02} \stackrel{?}{\Rightarrow} \tilde{L}_{10}\tilde{U}_{02} + u_{12}^T = a_{12}^T + \delta a_{12}^T$
- ▶ GEMV: $l_{21} := (a_{21} - L_{20}u_{01})/v_{11} \stackrel{?}{\Rightarrow} \tilde{L}_{20}\tilde{u}_{01} + l_{21}\tilde{v}_{11} = a_{21} + \delta a_{21}$

DOT: $\nu := (\beta - l^T x) / \lambda$ Inventory

Results built directly from the computational models

- $\lambda \tilde{\nu} = (\beta + \delta\beta) - (l + \delta l)^T x \quad \begin{cases} |\delta\beta| \leq \gamma_2 |\beta| \\ |\delta l| \leq \gamma_{n+2} |l| \end{cases}$
- $(\lambda + \delta\lambda) \tilde{\nu} = \beta - (l + \delta l)^T x \quad \begin{cases} |\delta\lambda| \leq \gamma_2 |\lambda| \\ |\delta l| \leq \gamma_n |l| \end{cases}$
- $(\lambda + \delta\lambda) \tilde{\nu} = (\beta + \delta\beta) - (l + \delta l)^T x \quad \begin{cases} |\delta\beta| \leq \gamma_1 |\beta| \\ |\delta l| \leq \gamma_{n+1} |l| \\ |\delta\lambda| \leq \gamma_1 |\lambda| \end{cases}$

GEMV: $w := (y - Ax) / \lambda$

Results built from those of DOT and Axdy.

• **Step #5:** Inductive step.

Application: fine-grain bounds

$$Lx = b \Rightarrow \begin{cases} (L + \Delta L)\tilde{x} = b \\ |\Delta L| \leq \gamma_n |L| \end{cases}, \text{ i.e., } |\Delta L| \leq \begin{bmatrix} \gamma_n & & 0 \\ & \ddots & \\ & & \gamma_n \end{bmatrix} \odot |L|$$

$\odot =$ pointwise multiplication

For some applications the factor γ_n is too coarse. The interest lays on how different variables affect/are affected by the computation.

Example: Algorithm TRSV

Partition $L \rightarrow \left(\begin{array}{c|c} L_{TL} & 0 \\ \hline L_{BL} & L_{BR} \end{array} \right), x \rightarrow \begin{pmatrix} x_T \\ x_B \end{pmatrix}, b \rightarrow \begin{pmatrix} b_T \\ b_B \end{pmatrix}$
where L_{TL} , x_T , and b_T are empty

While $m(x_T) < m(x)$ **do**

Repartition

$$\left(\begin{array}{c|c} L_{TL} & 0 \\ \hline L_{BL} & L_{BR} \end{array} \right) \rightarrow \left(\begin{array}{c|c|c} L_{00} & 0 & 0 \\ \hline l_{10}^T & \lambda_{11} & 0 \\ \hline L_{20} & l_{21} & L_{22} \end{array} \right), \dots$$

$$\chi_1 := (\beta_1 - l_{10}^T x_0) / \lambda_{11} \quad \text{DOT}(2)$$

Continue

$$\left(\begin{array}{c|c} L_{TL} & 0 \\ \hline L_{BL} & L_{BR} \end{array} \right) \leftarrow \left(\begin{array}{c|c|c} L_{00} & 0 & 0 \\ \hline l_{10}^T & \lambda_{11} & 0 \\ \hline L_{20} & l_{21} & L_{22} \end{array} \right), \dots$$

endwhile

Theorem: $|\Delta L| \leq T \odot |L|$,
where $T \leq \text{LowTriToeplitz}(\{\gamma_2, \gamma_2, \gamma_3, \dots, \gamma_n\}^T)$.
Proof: Using a different analysis for DOT. $[x^T y] = x^T y + x^T \Sigma^{(n)} y$,
where $\Sigma^{(n)} \leq \text{diag}(\{\gamma_n, \gamma_n, \gamma_{n-1}, \dots, \gamma_2\})$. Then

$$T = \begin{bmatrix} \gamma_2 & & & & & & \\ \gamma_1 & \gamma_2 & & & & & \\ \gamma_2 & \gamma_2 & \gamma_2 & & & & \\ \gamma_3 & \gamma_3 & \gamma_2 & \gamma_2 & & & \\ \vdots & & & & \ddots & & \\ \gamma_{n-1} & \gamma_{n-1} & \gamma_{n-2} & \dots & \gamma_2 & \gamma_2 & \end{bmatrix}$$