$\operatorname{span}(\boldsymbol{A}) \triangleq \{\alpha_1 \boldsymbol{x}_1 + \alpha_2 \boldsymbol{x}_2 + \dots + \alpha_k \boldsymbol{x}_k\} \begin{cases} \boldsymbol{x}_1, \boldsymbol{x}_2, \dots, \boldsymbol{x}_n \in \mathbb{C}^n \\ \alpha_1, \alpha_2, \dots, \alpha_n \in \mathbb{C} \end{cases}$ $\boldsymbol{A} = (\boldsymbol{x}_1, \boldsymbol{x}_2, \dots, \boldsymbol{x}_n)$

 $\begin{array}{ll} \textbf{Vec. Norms} \left\{ \begin{array}{ll} \|\boldsymbol{x}\|_1 = \sum\limits_{i=1}^n |x_i| & \|\boldsymbol{x}\|_2 = \left(\sum\limits_{i=1}^n |x_i|^2\right)^{1/2} \\ \|\boldsymbol{x}\|_\infty = \max\limits_{1 \leq i \leq n} |x_i| & \|\boldsymbol{x}\|_p = \left(\sum\limits_{i=1}^n |x_i|^p\right)^{1/p} \end{array} \right., & \|\gamma\boldsymbol{x}\| = |\gamma| \cdot \|\boldsymbol{x}\| \\ \dagger \ \ell^p\text{-norms in } \mathbb{R}^n, \ p = 1, 2, \infty \end{array}$

 $\text{Mat. Norms} \left\{ \begin{array}{ll} \|\boldsymbol{A}\|_1 = \max_{1 \leq j \leq n} \left(\sum_{i=1}^n |a_{ij}|\right) & \|\boldsymbol{A}\|_2 = \sqrt{\rho(A^TA)} & \|\boldsymbol{\gamma}\boldsymbol{A}\| \leq |\boldsymbol{\gamma}| \cdot \|\boldsymbol{A}\| \\ \|\boldsymbol{A}\|_{\infty} = \max_{1 \leq i \leq n} \left(\sum_{j=1}^n |a_{ij}|\right) & \|\boldsymbol{A}\|_F = \left(\sum_{i=1}^n \sum_{j=1}^n |a_{ij}|^2\right)^{1/2} & , & \|\boldsymbol{A}\boldsymbol{B}\| \leq \|\boldsymbol{A}\| + \|\boldsymbol{B}\| \\ & \|\boldsymbol{A}\boldsymbol{x}\| \leq \|\boldsymbol{A}\| \cdot \|\boldsymbol{x}\| \end{array} \right.$

 \dagger ℓ^p -norms in $\mathbb{R}^{n \times n}$, $p=1,2,\infty$ and Frobenius-norm

 $egin{array}{lll} ext{Special Mat.} & \left\{egin{array}{lll} ext{Hermitian} & : & A^* = A & ext{Unitary} & : & U^*U = UU^* = I \ ext{Normal} & : & A^*A = AA^* & ext{Orthogonal} & : & Q^TT = QQ^T = I \end{array}
ight.$

† eigval./vec. are only defined for square mat.

† real mat. may have comp. eigval./vec.

 \dagger algebraic multiplicity (AM) of $\lambda_i\colon \left\{k\in\mathbb{R}: \det(m{A}-\lambdam{I})=(\lambda-\lambda_i)^kg(\lambda)=0\right\}$

 \dagger geometric multiplicity (GM) of λ_i : dim. of λ_i 's eigenspace

 \dagger similar mat. ($oldsymbol{A} = oldsymbol{X} B oldsymbol{X}^{-1}$) have same eigval.

† mat. spctm.: $\sigma(\mathbf{A}) \triangleq \{\lambda_1, \dots, \lambda_n\}$

Similarity Trans.
$$\left\{ egin{array}{l} A = XBX^{-1} \ X^{-1}AX = B \end{array}
ight.$$

ullet Jordan Canonical From: $oldsymbol{A} \in \mathbb{R}^{n imes n}$, $oldsymbol{X} \in \mathbb{C}^{n imes n}$

$$oldsymbol{X}^{-1}Aoldsymbol{X} = egin{pmatrix} oldsymbol{J}_1 & & & & & \\ & oldsymbol{J}_2 & & & & \\ & & \ddots & & & \\ & & oldsymbol{J}_p \end{pmatrix} \;,\; oldsymbol{J}_i = egin{pmatrix} oldsymbol{J}_{i1} & & & & & \\ & oldsymbol{J}_{i2} & & & & \\ & & & \ddots & & \\ & & & oldsymbol{J}_{i
u_i} \end{pmatrix} \;,\; oldsymbol{J}_{ik} = egin{pmatrix} \lambda_i & 1 & & & \\ & \ddots & \ddots & & \\ & & \lambda_i & 1 \\ & & & \lambda_i \end{pmatrix}$$

- † ν_i : GM of λ_i
- \dagger $oldsymbol{J}_{ik}\colon$ Jordan block wrt. one eigvec.
- \dagger norm-mat. $m{A}^Tm{A} = m{A}m{A}^T \iff m{A}$ can be diagonalized and $m{X}$ is unit-mat.
- ullet Schur Decomposition/Triangulation: $oldsymbol{A} \in \mathbb{C}^{n imes n}$, $oldsymbol{U} \in \mathbb{C}^{n imes n}$

$$oldsymbol{U}^*oldsymbol{A}oldsymbol{U}=egin{pmatrix} \lambda_1 & r_{12} & \cdots & r_{1n} \ & \lambda_2 & \cdots & r_{2n} \ & & \ddots & dots \ & & & \lambda_n \end{pmatrix} riangleq oldsymbol{R} & \iff oldsymbol{A}=oldsymbol{U}oldsymbol{R}oldsymbol{U}^*$$

- \dagger simplest form of unitary trans., but U,R are not unique
- \dagger norm-mat. $A^*A=AA^*\Longleftrightarrow R$ is diag-mat.
- \dagger Hert-mat. $oldsymbol{A}^* = oldsymbol{A} \iff oldsymbol{R}$ is real diag-mat.
- ullet Schur Canonical Form: $oldsymbol{A} \in \mathbb{R}^{n imes n}$, $oldsymbol{Q} \in \mathbb{R}^{n imes n}$

$$Q^T A Q = T$$

- \dagger $m{T}$ is block-tridiag-mat. with $m{T}_{ii}$ of igg(1 imes1 : eigval. 2 imes2 : comp. conj. pair of eigvals.
- \dagger $\lambda_i \in \mathbb{R} \iff T = R$ is upper triang-mat. With λ_i on the diag.

$$\textbf{Pos. (Semi-)Def.} \left\{ \begin{array}{l} \textbf{Symm. Pos. (semi-)Def.} : & \forall \boldsymbol{x} \neq 0 \ \boldsymbol{x}^T \boldsymbol{A} \boldsymbol{x} > 0 \, (\geq 0) \ , \ \boldsymbol{A}^T = \boldsymbol{A} \in \mathbb{R}^{n \times n} \\ \textbf{Herm. Pos. (semi-)Def.} : & \forall \boldsymbol{x} \neq 0 \ \boldsymbol{x}^* \boldsymbol{A} \boldsymbol{x} > 0 \, (\geq 0) \ , \ \boldsymbol{A}^* = \boldsymbol{A} \in \mathbb{C}^{n \times n} \\ \textbf{Pos. (semi-)Def.} : & \forall \boldsymbol{x} \neq 0 \ \underbrace{\operatorname{Re}(\boldsymbol{x}^* \boldsymbol{A} \boldsymbol{x}) > 0 \, (\geq 0)}_{\infty} \end{array} \right.$$

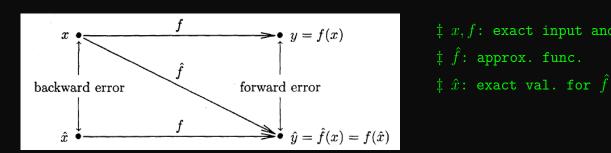
• arithmetic
$$\left\langle \begin{array}{l} \varepsilon(x_1+x_2) & \leq & \varepsilon(x_1)+\varepsilon(x_2) \\ \varepsilon(x_1x_2) & \leq & \left|x_2\right|\varepsilon(x_1)+\left|x_1\right|\varepsilon(x_2) \end{array} \right.$$
, $\left. \begin{array}{l} \varepsilon\left(\frac{x_1}{x_2}\right) & \leq & \frac{\left|x_1\right|\varepsilon(x_1)+\left|x_1\right|\varepsilon(x_2)}{\left|x_2\right|^2} \end{array} \right.$
• functional $\left\langle \begin{array}{l} \varepsilon\left(f(x)\right) & \lessapprox & \left|f'(x)\right|\varepsilon(x) \left[\mathbf{4},\mathbf{5}\right] \\ \varepsilon_r\left(f(x)\right) & = & \operatorname{cond} \cdot \varepsilon_r(x) \end{array} \right.$, $\left. \begin{array}{l} \operatorname{cond} & \triangleq & \left|\frac{\tilde{x}f'\left(\tilde{x}\right)}{f\left(\tilde{x}\right)}\right| \end{array} \right.$

• functional
$$\left\langle \begin{array}{l} \varepsilon\left(f(x)\right) & \lessapprox & \left|f'(x)\right| \varepsilon(x) \ [\mathbf{4},\mathbf{5}] \\ \varepsilon_r\left(f(x)\right) & = & \operatorname{cond} \cdot \varepsilon_r(x) \end{array} \right.$$
, $\operatorname{cond} \triangleq \left|\frac{\tilde{x}f'\left(\tilde{x}\right)}{f\left(\tilde{x}\right)}\right|$

$$\dagger \varepsilon(f(x)) \approx \sum_{k=1}^{n} \left| \frac{\partial f(x)}{\partial \tilde{x}_k} \right| \varepsilon(x_k) , f(x) = f(x_1, \dots, x_n)$$

† bound the err. rather than compute it (true val. unknown)

Err. Anly.
$$\begin{cases} \text{fore err.} & : \ \Delta y = \hat{y} - y = \hat{f}(x) - f(x) \\ \text{back err.} & : \ \Delta x = \hat{x} - x \text{ where } f(\hat{x}) = \hat{y} \end{cases}$$



 $\ddagger x, f \colon \texttt{exact input} \texttt{ and func}.$

$$\dagger \hat{f}(x) = f(\hat{x})$$
 due to the choice of \hat{x} , which defines \hat{x}

† back. err. anly is easier, used to measure algo. stability

$$\dagger \ \, \mathbf{total} \ \, \mathbf{err.} = \hat{f}(\hat{x}) - f(x) = \underbrace{\left(\hat{f}(\hat{x}) - f(\hat{x})\right)}_{\text{comp. err.}} + \underbrace{\left(f(\hat{x}) - f(x)\right)}_{\text{data err.}}$$

Cond. Num.

$$\operatorname{cond} \triangleq \frac{|\mathtt{rel. change in sol.}|}{|\mathtt{rel. change in input}|} = \frac{\left(f(\hat{x}) - f(x)\right)/f(x)}{\left(\hat{x} - x\right)/x} = \frac{|\Delta y/y|}{|\Delta x/x|}$$

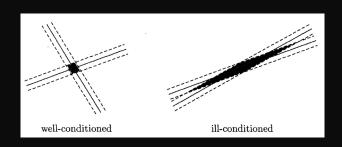
$$\dagger \text{ cond} \ge 1 \ (>10)$$
: sensi./ill-cond. prob.

† |rel. fore. err.|
$$\lesssim \text{cond} \cdot |\text{rel. back. err.}|$$

 \circ cond \iff amplification factor

 $\circ \lesssim$: upper bound for the max. cond.

$$\dagger \text{ cond } \approx \left| \frac{xf'(x)}{f(x)} \right| \ [6]$$



Err. Anly. Sum.

	Total Err.		
	comp. err.		data err.
	trunc. err.	round. err.	data eff.
howto est.	theoretical anly.	back. err. anly.	cond.ing, cond
		hard to quantify	
howto rdc.	aglo. selction	stable algo.	change prob. form.
		$tips^\dagger$, $dbl ext{-precs}$.	improve cond.ing

```
† avoid subtractive cancellation in nums. of nearly equal mag.
```

 \dagger adjust the order of additions

Mat. Cond.

$$\kappa(\boldsymbol{A}) \triangleq \|\boldsymbol{A}\| \cdot \|\boldsymbol{A}^{-1}\|$$

†
$$\kappa$$
 is def. for sqr. non-singlr. mat., $\kappa(\boldsymbol{A}) = \infty$ if \boldsymbol{A} singlr. † $\kappa(\boldsymbol{A}) \geq 1$, $\kappa(\boldsymbol{I}) = 1$, $\kappa(\gamma \boldsymbol{A}) = \kappa(\boldsymbol{A})$, $\kappa(\boldsymbol{D}) = (\max |d_i|) / (\min |d_i|)$, $\boldsymbol{D} = \operatorname{diag}(d_i)$

 $[\]dagger$ avoid adding large and small nums.

Err. Bounds

$$\frac{\|\Delta x\|}{\|x\|} \lessapprox \kappa_1(A) \frac{\|\Delta b\|}{\|b\|} \ [7] \quad , \quad \frac{\|\Delta x\|}{\|\hat{x}\|} \lessapprox \kappa_2(A) \frac{\|E\|}{\|A\|} \ [8] \quad , \quad \frac{\|\Delta x\|}{\|x\|} \lessapprox \kappa_3(A) \left(\frac{\|\Delta b\|}{\|b\|} + \frac{\|E\|}{\|A\|}\right) \ [9]$$

$$\uparrow \lessapprox : \text{ approx. bounded by}$$

$$\uparrow \kappa \text{ provides a quantitative bound for the err. in comp. sol.}$$

$$\uparrow \kappa_1 \text{ bounds the max. rel. change in sol. due to a given rel. change in vec. } b$$

$$\uparrow \text{ similar rst. } \kappa_2 \text{ holds for rel. change in mat. } A$$

$$\uparrow \text{ mat. scaling affects } \kappa \text{ rather than the singlr.}$$

 $\dagger \ rac{\|\hat{m{x}}-m{x}\|}{\|m{x}\|} \lessapprox \kappa(m{A})arepsilon_m$ if input data accurate to mach. precs.

Residual
$$\left\{egin{array}{l} r=b-A\hat{x} & ext{where } \hat{x} ext{ is approx. sol.} \\ ext{rel. res.} & extstyle & ext{} \frac{\|r\|}{\|A\|\cdot\|\hat{x}\|} \end{array}
ight.$$
 $\left. \frac{\|\Delta x\|}{\|\hat{x}\|} \leq \kappa(A) \frac{\|r\|}{\|A\|\cdot\|\hat{x}\|} \right. \left. \left[10 \right]
ight.$

† size of res. is considered rel. to the size of prob. and sol.

 \dagger small rel. res. \leadsto small rel. err. iff. $m{A}$ is well-cond.

 \dagger large rel. res. \leadsto large back. err. in mat. \leadsto unstable algo. [11]

 \dagger stable algo. \iff small rel. res. (irresp. to cond.ing)

Tri. Lin. Sys.

• lower tri. sys.
$$\left\langle \begin{array}{l} {m L}{m y}={m b} \end{array}
ight.$$
 $\left\langle \begin{array}{l} {m y}_1={m b}_1\Big/l_{11} \end{array}, \quad y_i=\left(b_i-\sum\limits_{j=1}^{i-1}l_{ij}y_j\right)\Big/l_{ii} \;,\;i=2,\cdots,n \end{array}
ight.$

Algorithm 1: Fore. Subs. for Unit Lower Tri. Mat.

```
_2 for i \leftarrow 2 to n do
     for j \leftarrow 1 to i-1 do
```

• upper tri. sys.
$$\left\langle \begin{array}{l} m{U}m{x} = m{y} \\ x_n = y_n \Big/ u_{nn} \end{array} \right.$$
 , $x_i = \left(y_i - \sum_{j=i+1}^n u_{ij} x_j \right) \Big/ u_{ii}$, $i = n-1, \cdots, 1$

Algorithm 2: Back. Subs. for Upper Tri. Mat.

```
2 for i \leftarrow n-1 to 1 do
      for j \leftarrow i+1 to n do
```

Perm. Mat.

$$\mathbf{P}^{-1} = \mathbf{P}^{T}$$
 , $\|\mathbf{P}\| = 1$, $\kappa(\mathbf{P}) = 1$, $\kappa(\mathbf{P}\mathbf{A}) = \kappa(\mathbf{A})$

- \dagger P is sqr. mat. with only one 1 in each row/col. and is always non-singlr.
- \dagger P is orthogonal mat., prod. of P is also perm. mat.
- \dagger PA reorders rows, AP reorders cols.

Elem. Elim. Mat.

$$\boldsymbol{M}_{k}\boldsymbol{a} = \begin{pmatrix} 1 & \cdots & 0 & 0 & \cdots & 0 \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 0 & \cdots & 1 & 0 & \cdots & 0 \\ 0 & \cdots & -m_{k+1} & 1 & \cdots & 0 \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 0 & \cdots & -m_{n} & 0 & \cdots & 1 \end{pmatrix} \begin{pmatrix} a_{1} \\ \vdots \\ a_{k} \\ a_{k+1} \\ \vdots \\ a_{n} \end{pmatrix} = \begin{pmatrix} a_{1} \\ \vdots \\ a_{k} \\ 0 \\ \vdots \\ 0 \end{pmatrix}, \quad m_{i} = a_{i}/a_{k} \\ 0 \\ \vdots \\ 0 \end{pmatrix}$$

 \dagger $m{M}_k$ is unit lower tri., non-singlr., annihilates all entries below **pivot** $a_k \neq 0$

$$\ \, \dagger \ \, \boldsymbol{M}_k = \boldsymbol{I} - \boldsymbol{m}\boldsymbol{e}_k^T \\ \ \, \boldsymbol{M}_k^{-1} = \boldsymbol{I} + \boldsymbol{m}\boldsymbol{e}_k^T \triangleq \boldsymbol{L}_k \ \, \middle\rangle \ \, \text{rever sed signs of multipliers} \\ \ \, \boldsymbol{m}_k^{-1} = \boldsymbol{I} + \boldsymbol{m}\boldsymbol{e}_k^T \triangleq \boldsymbol{L}_k \ \, \middle\rangle$$

 \dagger $m{M}_km{M}_i~(j>k)$ is their "union", and similar rst. holds for $m{L}_km{L}_i~[13]$

 ${m L}{m U}$ Fact. by Gauss. Elim.

$$\underbrace{M_{n-1}\cdots M_1}_{\text{lower tri. mat.}M} Ax = \underbrace{MAx}_{U} = \underbrace{Mb}_{y} \quad , \quad LUx = b \quad \left\langle \begin{array}{c} Ly = b & : \text{ fore. subs.} \\ Ux = y & : \text{ back. subs.} \end{array} \right|_{1}$$

 \dagger LU Fact. is unique \iff $\left\langle egin{array}{c} L$ is unit lower tri., U is upper tri. all leading principle submats. are non-singlr.

 \dagger Gauss. Elim. and LU Fact. are two ways of expressing same process

† zero pivot causes breakdown \leadsto chooes entry with large mag.

Pivoting

- partial pvt.
 - \dagger $oldsymbol{M}^{-1}$ is not necessarily lower tri. due to perm.
 - \dagger $oldsymbol{P}oldsymbol{A} = oldsymbol{L}oldsymbol{U}$ where $oldsymbol{P} = oldsymbol{P}_{n-1}\cdotsoldsymbol{P}_1$, but can't be determined in advance
 - \dagger universally used since N.S. is more than adaquate
- complete pvt.
 - $\ensuremath{^{\dagger}}$ entire remaining unreduced submats. is searched for the max. mag.
 - \dagger PAQ=LU, theoretically superior, but much expensive

${m L}{m U}$ Fact. Stability

$$\frac{\|r\|}{\|A\|\cdot\|\hat{x}\|} \leq \frac{\|E\|}{\|A\|} \leq \rho\, n\, \varepsilon_m \quad \text{[11], [Wi161]}$$

 † E : back. err. of mat. A
 † growth fac. $\rho \triangleq \frac{\max. \text{ ele. of } U}{\max. \text{ ele. of } A} \left\langle \begin{array}{l} \text{without pvt.} & : \text{ arbitrarily large} \leadsto \text{unstable} \\ \text{partial pvt.} & : \rho \leq 2^{n-1} \; (<10) \leadsto \text{stable} \\ \text{complete pvt.} & : \rho \; \text{much smaller but not worth} \\ \\ \dagger \frac{\|E\|}{\|A\|} \lessapprox n\, \varepsilon_m \; \text{in practice} \overset{\text{always}}{\leadsto} \; \text{small res. regardless of cond.ing} \\ \dagger \; \text{small res.} \iff \text{accurate sol. unless } A \; \text{is well-cond.}$

${\it LU}$ Fact. Algo.

```
† fact. effectively in-place
```

 \dagger trans. of b can be included or as a sep. step

- ullet storage anly. $\left\{egin{array}{ll} L,U ext{ overwrite init. mat. } A & U ext{ on strict lower tri.} \ & L ext{ on strict lower tri.} \ & ext{aux. vec. } p ext{ keeps track of new row order} \end{array}
 ight.$
- ullet complexity anly.: $rac{2}{3}n^3+\mathcal{O}(n^2)$ [14]

```
\textbf{Symm. Pos. Def. Sys.} \begin{cases} \text{ all eigvals. are pos.} \\ \text{all leading principle mats. are SPD} \\ \text{all elems. on diag. are pos., and } \max_i \{a_{ii}\} > \max_{i \neq j} \{|a_{ij}|\} \\ \text{ Cholesky Fact.: } A = LL^T \end{cases}
```

Cholesky Fact.

 $\bullet \ \boldsymbol{A} = \boldsymbol{L}\boldsymbol{L}^T$

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

$$a_{ij} = \sum_{k=1}^{n} l_{ik} l_{jk} = l_{jj} l_{ij} + \sum_{k=1}^{j-1} l_{ik} l_{jk} , \quad i, j = 1, 2, \cdots, n$$

Algorithm 4: Cholesky $oldsymbol{L}oldsymbol{L}^T$ Fact

```
1 for j \leftarrow 1 to n do
2 a_{jj} \leftarrow \left(a_{jj} - \sum_{k=1}^{j-1} a_{jk}^2\right)^{1/2}; // diag. elem.
3 for i \leftarrow j+1 to n do
4 a_{ij} \leftarrow \left(a_{ij} - \sum_{k=1}^{j-1} a_{ik} a_{jk}\right)/a_{jj}; // elems. below diag. elem.
```

 \dagger $m{A} = m{L}m{L}^T$ is unique when diag. ele. are required to be pos.

 \dagger sqr. roots are all of pos. \leadsto algo is well-def. \leadsto no pvt. for N.S.: $\rho \leq 1 \; [15]$

 \dagger only access, store, overwrite lower tri. mat. of A

$$\dagger \ \frac{1}{3} n^3 + \mathcal{O}(n^2) \ [extbf{16}]$$
 (half of $m{L}m{U}$ fact.); $egin{bmatrix} \mathtt{mcmd.: chol}(m{A}) \end{bmatrix}$

 $\bullet \ \ \boldsymbol{A} = \boldsymbol{L}\boldsymbol{D}\boldsymbol{L}^T$

$$\begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{pmatrix} = \begin{pmatrix} 1 \\ l_{21} & 1 \\ \vdots & \ddots & \ddots \\ l_{n1} & \cdots & l_{n,n-1} & 1 \end{pmatrix} \begin{pmatrix} d_1 \\ d_2 \\ & \ddots \\ & d_n \end{pmatrix} \begin{pmatrix} 1 & l_{21} & \cdots & l_{n1} \\ 1 & \cdots & l_{n2} \\ & & \ddots & \vdots \\ & & & 1 \end{pmatrix}$$

$$a_{ij} = \sum_{k=1}^{n} l_{ik} d_k l_{jk} = d_j l_{ij} + \sum_{k=1}^{j-1} l_{ik} d_k l_{jk} , \quad i, j = 1, 2, \cdots, n$$

Algorithm 5: Cholesky $oldsymbol{L} oldsymbol{D} oldsymbol{L}^T$ Fact.

```
1 for j \leftarrow 1 to n do

2 a_{jj} \leftarrow a_{jj} - \sum_{k=1}^{j-1} a_{jk}^2 a_{kk}; // diag. elem.

3 for i \leftarrow j+1 to n do

4 a_{ij} \leftarrow \left(a_{ij} - \sum_{k=1}^{j-1} a_{ik} a_{kk} a_{jk}\right)/a_{jj}; // elems. below diag. elem.
```

† advantage of not requiring any sqr. roots.

 \dagger d_i in $m{L}m{D}m{L}^T$ is the sqr. of l_{ii} in $m{L}m{L}^T$

Symm. inDef. Lin. Sys.

 \dagger $ho_{chol}\gg 1$ \leadsto breakdown using Cholesky fact. \leadsto unstable algo.

$$\dagger$$
 pvt. \leadsto asymm. \Longrightarrow \Longrightarrow symm.: $m{PAP}^T = m{LDL}^T$

$$m{PAP^T = Lm{T}L^T}$$
 , $m{T}$ is symm. tri. mat. [Aas71] $m{\uparrow}$ stable $igg \langle m{PAP^T = Lm{ ilde{D}}L^T}$, $m{ ilde{D}}$ is block tridiag. mat. $m{igg \langle} 1 imes 1$ [BK77]

Tridiag. Lin. Sys.

$$\boldsymbol{A} = \begin{pmatrix} d_1 & u_1 & & & \\ l_2 & \ddots & \ddots & & \\ & \ddots & \ddots & u_{n-1} \\ & & l_n & d_n \end{pmatrix} \quad , \quad \begin{aligned} |d_1| > |u_1| > 0 & & \ddagger > : & \text{irr. strict diag. dom. mat.} \\ |d_i| > |l_i| > 0 & & \ddagger > : & \text{irr. weak diag. dom. mat.} \end{aligned}$$

$$\boldsymbol{A} = \begin{pmatrix} d_1 & u_1 & & & \\ l_2 & \ddots & \ddots & & \\ & \ddots & \ddots & u_{n-1} \\ & & l_n & d_n \end{pmatrix} = \begin{pmatrix} \alpha_1 & & & & \\ l_2 & \alpha_2 & & & \\ & \ddots & \ddots & & \\ & & l_n & \alpha_n \end{pmatrix} \begin{pmatrix} 1 & \beta_1 & & & \\ & 1 & \ddots & & \\ & & \ddots & \ddots & \\ & & & l_n & \alpha_n \end{pmatrix} \begin{pmatrix} 1 & \beta_1 & & & \\ & 1 & \ddots & & \\ & & \ddots & \beta_{n-1} \\ & & & 1 \end{pmatrix} \stackrel{\alpha_i = d_i - l_i \beta_{i-1}}{\underset{\boldsymbol{\lambda} = u_i}{\boldsymbol{\lambda}}} \boldsymbol{A} \begin{pmatrix} \boldsymbol{\beta}_0 = 0 \\ \boldsymbol{\beta}_0 = 0 \end{pmatrix} \boldsymbol{A} \begin{pmatrix} \boldsymbol{\beta}_0 = 0 \\ \boldsymbol{\beta}_0 = 0 \end{pmatrix} \boldsymbol{A} \begin{pmatrix} \boldsymbol{\beta}_0 = 0 \\ \boldsymbol{\beta}_0 = 0 \end{pmatrix} \boldsymbol{A} \begin{pmatrix} \boldsymbol{\beta}_0 = 0 \\ \boldsymbol{\beta}_0 = 0 \end{pmatrix} \boldsymbol{A} 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$$\boldsymbol{A}\boldsymbol{x} = \boldsymbol{b} \Rightarrow \boldsymbol{L}\boldsymbol{U}\boldsymbol{x} = \boldsymbol{b} \begin{cases} \boldsymbol{L}\boldsymbol{y} = \boldsymbol{b} & \Rightarrow & y_i = (b_i - l_i y_{i-1})/\alpha_i &, i = 1, \dots, n, y_0 = 0 \\ \boldsymbol{U}\boldsymbol{x} = \boldsymbol{y} & \Rightarrow & x_i = (y_i - \beta_i x_{i+1}) &, i = n, \dots, 1, x_{n+1} = 0 \end{cases}$$

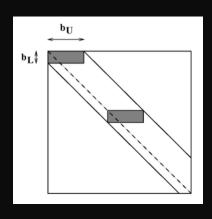
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Algorithm 6: Thomas Algo. for Tridiag. Lin. Sys.
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\dagger 0<|eta_i|<1 \leadsto err. in back. subs. is under control \dagger 0<|d_i|-|l_i|<|lpha_i|<|d_i|+|l_i| , i=2,3,\cdots,n \leadsto lpha_i\neq 0
```

 \dagger solve $m{Ly}=m{b}$ and $m{LU}$ fact. simultaneously \leadsto no need to store $lpha_i$ but eta_i \dagger complexity: 8n $m{[17]}$

Banded Tri. Lin. Sys.

$$a_{ij} = 0 \quad \text{for } \left\{ \begin{array}{l} i > j + b_L \\ i < j - b_U \end{array} \right.$$



$$ullet$$
 partial pvt. $\left : lower band $=b_L$ with at most b_L+1 nz. in each col. $m{U}$: upper band $\leq b_L+b_U$$

† complexity: $2nb_Lb_U + 2n(b_L + b_U)$

Pertb. Anly.

$$egin{aligned} egin{aligned} oldsymbol{Ax} = oldsymbol{b} \ (oldsymbol{A} + oldsymbol{\delta A}) oldsymbol{x}^* = oldsymbol{b} + oldsymbol{\delta b} \ oldsymbol{r} = oldsymbol{b} - oldsymbol{Ax}^* \end{aligned} egin{aligned} oldsymbol{\delta x} = oldsymbol{x}^* - oldsymbol{x} \ = -oldsymbol{A}^{-1} oldsymbol{r} \left[oldsymbol{18}
ight] \end{aligned} egin{aligned} oldsymbol{x} : & ext{exact sol.} \ oldsymbol{x}^* : & ext{approx. sol.} \ oldsymbol{r} : & ext{res.} \end{aligned}$$

• $\delta x \longleftrightarrow x^*$ (A is non-singlr.)

$$egin{aligned} & \frac{\| oldsymbol{\delta x} \|}{\| oldsymbol{x}^* \|} \leq \| oldsymbol{A}^{-1} \| \cdot \| oldsymbol{A} \| \cdot \left(\frac{\| oldsymbol{\delta A} \|}{\| oldsymbol{A} \|} + \frac{\| oldsymbol{\delta b} \|}{\| oldsymbol{A} \| \cdot \| oldsymbol{x}^* \|}
ight) \ & \frac{\| oldsymbol{\delta x} \|}{\| oldsymbol{x}^* \|} \leq \kappa(oldsymbol{A}) \cdot \frac{\| oldsymbol{\delta A} \|}{\| oldsymbol{A} \|} \ \ ext{when} \ \ \| oldsymbol{\delta b} \| = 0 \end{aligned}$$

ullet $oldsymbol{\delta x} \leftrightsquigarrow oldsymbol{x}$ ($oldsymbol{A}$ is non-singlr., $\|oldsymbol{A}^{-1}\| \cdot \|oldsymbol{\delta A}\| < 1$)

$$\frac{\|\boldsymbol{\delta}\boldsymbol{x}\|}{\|\boldsymbol{x}\|} \le \frac{\kappa(\boldsymbol{A})}{1 - \kappa(\boldsymbol{A}) \cdot \frac{\|\boldsymbol{\delta}\boldsymbol{A}\|}{\|\boldsymbol{A}\|}} \cdot \left(\frac{\|\boldsymbol{\delta}\boldsymbol{A}\|}{\|\boldsymbol{A}\|} + \frac{\|\boldsymbol{\delta}\boldsymbol{b}\|}{\|\boldsymbol{b}\|}\right) [20]$$

$$\frac{1}{\kappa(\boldsymbol{A})} \cdot \frac{\|\boldsymbol{\delta}\boldsymbol{b}\|}{\|\boldsymbol{b}\|} \leq \frac{\|\boldsymbol{\delta}\boldsymbol{x}\|}{\|\boldsymbol{x}\|} \leq \kappa(\boldsymbol{A}) \cdot \frac{\|\boldsymbol{\delta}\boldsymbol{b}\|}{\|\boldsymbol{b}\|} \ \text{when} \ \|\boldsymbol{\delta}\boldsymbol{A}\| = 0$$

• $\delta x \leftrightarrow r$ (A is non-singlr.)

$$\|oldsymbol{\delta x}\| \le \|oldsymbol{A}^{-1}\| \cdot \|oldsymbol{r}\| \ [18]$$

Accuracy Imprv.

- scaling
 - \dagger scale by multiplying a diag. mat. $D\colon DADy=Db$, x=Dy;
 - † scaling affects cond.ing; not practical but worth trying for ill-cond. sys.
 - † accuracy is usually enhanced if all entries have abt. same order of mag.
- ullet iter. refine. $\left\{ egin{array}{ll} ext{calc. res. } r ext{ for approx. sol. } x \colon r = b Ax^* \ & ext{sol. } Az = r \ [21] ext{ with two tri. lin. sys. } [22] : \mathcal{O}(n^2) \end{array}
 ight.$

7 until x^* converges;

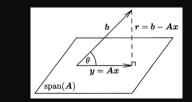
 \dagger x^*+z is the exact sol., but z^* is found in practice \dagger $\|r-Az^*\|$ is smaller than $\|r\|\leadsto x^*+z^*$ is closer to exact sol. than x^* \dagger A can not be overwritten \bullet A,L,U are stored

Lin. LSQ. Prob.

$$\boldsymbol{A}\boldsymbol{x}\cong\boldsymbol{b} \Leftrightarrow \min_{\boldsymbol{x}\in\mathbb{R}^n}\|\boldsymbol{b}-\boldsymbol{A}\boldsymbol{x}\|_2 = \min_{\boldsymbol{x}\in\mathbb{R}^n}\|\boldsymbol{r}\|_2 \quad \begin{cases} m=n \ : \ \boldsymbol{x}=\boldsymbol{A}^{-1}\boldsymbol{b} \ \text{if } \boldsymbol{A} \ \text{is non-singlr.} \\ m>n \ : \ \text{overdet.} \ \text{(in most cases)} \\ m< n \ : \ \text{underdet.} \end{cases}$$
 † uniqueness: sol. to $\boldsymbol{A}\boldsymbol{x}\cong\boldsymbol{b}$ is unique iff. \boldsymbol{A} is full col. rank: rank(\boldsymbol{A}) = n † existence: sol. always exists but not unique if \boldsymbol{A} is rank-deficient

Cond.ing of Lin. LSQ. Prob.

- ullet pseudoinv. for non-singlr. mat.: $oldsymbol{A}^+ riangleq (oldsymbol{A}^Toldsymbol{A})^{-1}oldsymbol{A}^T$
- cond. num. $\left\langle \begin{array}{l} \text{full col. rank} : \kappa(\pmb{A}) \triangleq \|\pmb{A}\| \cdot \|\pmb{A}^+\| \\ \text{defective rank} : \kappa(A) = \infty \end{array} \right.$



Sensitivity of Lin. LSQ. Prob.

$$\text{pertb. in } \boldsymbol{b} \quad : \quad \frac{\|\Delta \boldsymbol{x}\|}{\|\boldsymbol{x}\|} \leq \kappa(\boldsymbol{A}) \cdot \frac{1}{\cos \theta} \cdot \frac{\|\Delta \boldsymbol{b}\|}{\|\boldsymbol{b}\|} \tag{23}$$

$$\mathtt{pertb.\ in}\ \boldsymbol{A}\ :\ \frac{\|\Delta\boldsymbol{x}\|}{\|\boldsymbol{x}\|} \lessapprox \left(\kappa^2(\boldsymbol{A}) \cdot \tan\theta + \kappa(\boldsymbol{A})\right) \cdot \frac{\|\boldsymbol{E}\|}{\|\boldsymbol{A}\|} \ \ [24]$$

LSQ. Prob. Trans.

$$Ax \cong b \leadsto$$
 sqr. lin. sys. \leadsto tri. lin. sys. $\left\{ egin{array}{ll} 1) & {
m normal \ eq.} & : & {
m fastest} \end{array}
ight.$ 2) QR Fact. : most important 3) SVD Fact. : slowest but most reliable

Normal Eq.

$$A \in \mathbb{R}^{m imes n} \ (m \geq n), \ x^* \in \mathbb{R}^n \ \text{is lsq. sol.} \ \ \inf f. \ r = b - Ax^* \perp \operatorname{Ran}(A)$$
 $\Rightarrow \left\langle \begin{array}{l} A^T A x = A^T b & : \ \operatorname{lsq. prob. sol.} \iff \operatorname{normal eq. sol.} \\ A^T (b - A x) = 0 & : \ \operatorname{res.} \ r = b - Ax \ \operatorname{is ortho.} \ \operatorname{to span}(A) \ (\operatorname{geo. view}) \end{array}
ight.$ $\dagger \ rect. \ \operatorname{mat.} \ \leadsto \operatorname{sqr. mat.} \ \leadsto \operatorname{tri. mat.}$ $\left\{ \begin{array}{l} A^T A \ \operatorname{is symm. pos. def.} \\ \operatorname{unique lsq. sol.:} \ x = (A^T A)^{-1} A^T b \\ \operatorname{Cholesky Fact.:} \ A^T A = L L^T \Rightarrow \left\langle \begin{array}{l} L y = A^T b \\ L^T x = y \end{array} \right. \right.$ $\circ \ \operatorname{info. can be lost in forming} \ A^T A \ \operatorname{and} \ A^T b$ $\circ \ \operatorname{cond. num. is sqr. of} \ \kappa(A) \colon \ \kappa(A^T A) = \kappa^2(A) \ \leadsto \ \operatorname{unstable algo.}$

 \dagger Chol. Fact. complexity of $m{A}^Tm{A}$: $mn^2+rac{1}{2}n^3+\mathcal{O}(n^2)$ [26]

 $egin{aligned} oldsymbol{QR} & ext{Fact.} & igg ' & ext{orthornormal / unitary mat.} & oldsymbol{A} = oldsymbol{QR} \ R & : ext{ upper tri. mat} & (oldsymbol{A} \in \mathbb{C}^{m imes n}, m \geq n) \end{aligned}$ $\ \ \, \dagger ext{ existence:} & \exists oldsymbol{Q} \in \mathbb{C}^{m imes n} \left(oldsymbol{Q}^* oldsymbol{Q} = oldsymbol{I}
ight) \;, \; oldsymbol{R} \in \mathbb{C}^{n imes n} \left(r_{ij} = 0, i > j
ight)$ $\ \, \dagger ext{ uniqueness:} \; oldsymbol{QR} \; ext{fact.} \; ext{ is unique iff.} \; oldsymbol{A} \; ext{ is full col. rank, and } r_{ii} > 0 \ \ \, \dagger \; ext{app:} \; ^1) ext{lin.} \; ext{lsq. prob.} \; ; \; ^2) \; ext{eigval. prob.} \; ; \; ^3) \; oldsymbol{Ax} = oldsymbol{b} \; \text{ when } oldsymbol{A} \; \text{ is non-singlr. sqr. mat.} \end{aligned}$

QR Fact. \iff Lin. LSQ. Prob.

$$\begin{vmatrix}
A_{m \times n} = Q_{m \times n} R_{n \times n} \\
(Q, \hat{Q}) \in \mathbb{R}^{m \times m}
\end{vmatrix} \Rightarrow \|Ax - b\|_{2}^{2} = \|(Q, \hat{Q})^{T} \cdot (Ax - b)\|_{2}^{2} = \|\begin{pmatrix} Q^{T} \\ \hat{Q}^{T} \end{pmatrix} \cdot (QRx - b)\|_{2}^{2}$$

$$= \|\begin{pmatrix} Rx - Q^{T}b \\ -\hat{Q}^{T}b \end{pmatrix}\|_{2}^{2} = \|Rx - Q^{T}b\|_{2}^{2} + \|\hat{Q}^{T}b\|_{2}^{2} \ge \|\hat{Q}^{T}b\|_{2}^{2} \Rightarrow x^{*} = R^{-1}Q^{T}b$$

$$A_{m \times n} = Q_{m \times n} R_{n \times n} , b = (QQ^T + I - QQ^T)b$$

$$\Rightarrow Ax - b = Ax - (QQ^T + I - QQ^T)b = (Ax - QQ^Tb) - (I - QQ^T)b$$

$$\uparrow \Rightarrow \|Ax - b\|_2^2 = \|Ax - QQ^Tb\|_2^2 + \|(I - QQ^T)b\|_2^2 = \|Q(Rx - Q^Tb)\|_2^2 + \|(I - QQ^T)b\|_2^2$$

$$\geq \|(I - QQ^T)b\|_2^2 \Rightarrow x^* = R^{-1}Q^Tb$$

(3)
$$x^* = (A^T A)^{-1} A^T b = (R^T \underbrace{Q^T Q}_{I_{n \times n}} R)^{-1} R^T Q^T b = R^{-1} R^T R^T Q^T b = R^{-1} Q^T b$$

(4)
$$f(x) = f(a) + f'(a)(x-a) + \frac{f''(a)}{2!}(x-a)^2 + \frac{f^{(3)}(a)}{3!}(x-a)^3 + \dots + \frac{f^{(n)}(a)}{n!}(x-a)^n + \dots$$

$$(5) \quad f(x) - f(\tilde{x}) \approx f'(\tilde{x})(x - \tilde{x}) + \frac{1}{2}f'(\tilde{\xi})(x - \tilde{x})^2 \underset{|e| = |x - \tilde{x}| \le \varepsilon}{\Longrightarrow} \varepsilon \left(f(x) \right) \le |f'(\tilde{x})| \varepsilon(x) + \frac{|f''(\xi)|}{2} \varepsilon^2(x) \\ \lessapprox |f'(\tilde{x})| \varepsilon(x) \underset{f'(\tilde{x}) \approx f'(\tilde{x})}{\Longrightarrow} |f'(x)| \varepsilon(x)$$

(6)
$$\frac{\Delta y}{y} = \frac{f(x + \Delta x) - f(x)}{f(x)} \approx \frac{f'(x)\Delta x}{f(x)} \Longrightarrow \text{cond} \approx \frac{|\Delta y/y|}{|\Delta x/x|} = \frac{|xf'(x)|}{|f(x)|}$$

$$\begin{array}{ccc}
 & \mathbf{A}\mathbf{x} = \mathbf{b} \\
(7) & \mathbf{A}\hat{\mathbf{x}} = \mathbf{b} + \Delta \mathbf{b}
\end{array} \xrightarrow{\Delta \mathbf{x} = \hat{\mathbf{x}} - \mathbf{x}} \mathbf{A}\Delta \mathbf{x} = \Delta \mathbf{b} \\
\|\mathbf{b}\| = \|\mathbf{A}\mathbf{x}\| \le \|\mathbf{A}\| \cdot \|\mathbf{x}\| \\
\|\Delta \mathbf{x}\| = \|\mathbf{A}^{-1}\mathbf{b}\| \le \|\mathbf{A}^{-1}\| \cdot \|\Delta \mathbf{b}\|
\end{array} \Rightarrow \frac{\|\Delta \mathbf{x}\|}{\|\mathbf{x}\|} \le \|\mathbf{A}^{-1}\| \cdot \|\Delta \mathbf{b}\| \cdot \frac{\|\mathbf{A}\|}{\|\mathbf{b}\|} = \kappa(\mathbf{A}) \frac{\|\Delta \mathbf{b}\|}{\|\mathbf{b}\|}$$

$$\begin{array}{c}
\boldsymbol{A}\boldsymbol{x} = \boldsymbol{b} \\
(8) \quad (\boldsymbol{A} + \boldsymbol{E})\hat{\boldsymbol{x}} = \boldsymbol{b}
\end{array} \Rightarrow \Delta \boldsymbol{x} = \hat{\boldsymbol{x}} - \boldsymbol{x} = \boldsymbol{A}^{-1}(\boldsymbol{A}\hat{\boldsymbol{x}} - \boldsymbol{b}) = \boldsymbol{A}^{-1}(-\boldsymbol{E}\hat{\boldsymbol{x}}) = -\boldsymbol{A}^{-1}\boldsymbol{E}\hat{\boldsymbol{x}} \\
\Rightarrow \|\Delta \boldsymbol{x}\| \le \|\boldsymbol{A}^{-1}\| \cdot \|\boldsymbol{E}\| \cdot \|\hat{\boldsymbol{x}}\| \Rightarrow \frac{\|\Delta \boldsymbol{x}\|}{\|\hat{\boldsymbol{x}}\|} \le \kappa(\boldsymbol{A}) \frac{\|\boldsymbol{E}\|}{\|\boldsymbol{A}\|}$$

(9)
$$\begin{vmatrix} \mathbf{A}\mathbf{x} = \mathbf{b} \\ (\mathbf{A} + \mathbf{E})\hat{\mathbf{x}} = \mathbf{b} + \Delta \mathbf{b} \end{vmatrix} \Rightarrow \Delta \mathbf{x} = \hat{\mathbf{x}} - \mathbf{x} = \mathbf{A}^{-1}(\mathbf{A}\hat{\mathbf{x}} - \mathbf{b}) = \mathbf{A}^{-1}(\Delta \mathbf{b} - \mathbf{E}\hat{\mathbf{x}})$$

$$\Rightarrow \|\Delta \mathbf{x}\| \leq \|\mathbf{A}^{-1}\Delta \mathbf{b}\| + \|\mathbf{A}^{-1}\mathbf{E}\hat{\mathbf{x}}\| \leq \|\mathbf{A}^{-1}\| \cdot \|\Delta \mathbf{b}\| + \|\mathbf{A}^{-1}\| \cdot \|\mathbf{E}\| \cdot \|\mathbf{x}\|$$

$$\Rightarrow \frac{\Delta \mathbf{x}}{\|\mathbf{x}\|} \leq \frac{\|\mathbf{A}\| \cdot \|\mathbf{A}^{-1}\| \cdot \|\Delta \mathbf{b}\|}{\|\mathbf{A}\| \cdot \|\mathbf{x}\|} + \frac{\|\mathbf{A}\| \cdot \|\mathbf{A}^{-1}\| \cdot \|\mathbf{E}\|}{\|\mathbf{A}\|} = \kappa(\mathbf{A}) \left(\frac{\|\Delta \mathbf{b}\|}{\|\mathbf{b}\|} + \frac{\|\mathbf{E}\|}{\|\mathbf{A}\|}\right)$$

(10)
$$\|\Delta x\| = \|\hat{x} - x\| = \|A^{-1}(A\hat{x} - b)\| \\ = \\ \|A^{-1}(-r)\| \le \|A^{-1}\| \cdot \|r\| \ \ \} \Rightarrow \frac{\|\Delta x\|}{\|x\|} \le \frac{\|A\| \cdot \|A^{-1}\| \cdot \|r\|}{\|A\| \cdot \|x\|} = \kappa(A) \frac{\|r\|}{\|A\| \cdot \|x\|}$$

$$(11) ||(A + E)\hat{x} = b \Rightarrow ||r|| = ||b - A\hat{x}|| = ||E\hat{x}|| \le ||E|| \cdot ||\hat{x}|| \Rightarrow \frac{||r||}{||A|| \cdot ||\hat{x}||} \le \frac{||E||}{||A||}$$

(12)
$$MA = U \ A = LU$$
 $\Rightarrow L = M^{-1} = (M_{n-1} \cdots M_1)^{-1} = M_1^{-1} \cdots M_{n-1}^{-1} = L_1 \cdots L_{n-1}$

(13)
$$M_k M_j = \left(\boldsymbol{I} - \boldsymbol{m} \boldsymbol{e}_k^T \right) \left(\boldsymbol{I} - \boldsymbol{t} \boldsymbol{e}_j^T \right) = \boldsymbol{I} - \boldsymbol{t} \boldsymbol{e}_j^T - \boldsymbol{m} \boldsymbol{e}_k^T + \boldsymbol{m} \boldsymbol{e}_k^T \boldsymbol{t} \boldsymbol{e}_j^T \right) \stackrel{\boldsymbol{e}_k^T \boldsymbol{t} = 0}{=} \left\langle \boldsymbol{I} - \boldsymbol{t} \boldsymbol{e}_j^T - \boldsymbol{m} \boldsymbol{e}_k^T \right.$$

$$\boldsymbol{L}_k \boldsymbol{L}_j = \left(\boldsymbol{I} + \boldsymbol{m} \boldsymbol{e}_k^T \right) \left(\boldsymbol{I} + \boldsymbol{t} \boldsymbol{e}_j^T \right) = \boldsymbol{I} + \boldsymbol{t} \boldsymbol{e}_j^T + \boldsymbol{m} \boldsymbol{e}_k^T + \boldsymbol{m} \boldsymbol{e}_k^T \boldsymbol{t} \boldsymbol{e}_j^T \right) \stackrel{\boldsymbol{e}_k^T \boldsymbol{t} = 0}{=} \left\langle \boldsymbol{I} - \boldsymbol{t} \boldsymbol{e}_j^T - \boldsymbol{m} \boldsymbol{e}_k^T \right.$$

$$\boldsymbol{I} + \boldsymbol{t} \boldsymbol{e}_j^T + \boldsymbol{m} \boldsymbol{e}_k^T \boldsymbol{e}_j^T + \boldsymbol{m} \boldsymbol{e}_k^T \boldsymbol{e}_j^T \right\rangle \stackrel{\boldsymbol{e}_k^T \boldsymbol{t} = 0}{=} \left\langle \boldsymbol{I} - \boldsymbol{t} \boldsymbol{e}_j^T - \boldsymbol{m} \boldsymbol{e}_k^T \boldsymbol{e}_j^T \right.$$

(14)
$$O_{1u} = \sum_{i=1}^{n-1} \left(\sum_{j=i+1}^{n} 1 + \sum_{j=i+1}^{n} \sum_{k=i+1}^{n} 2 \right) = \sum_{i=1}^{n-1} \left(n - i + 2(n-i)^2 \right) = \frac{n(n-1)}{2} + 2\frac{n(n-1)(2n-1)}{6}$$

$$= \frac{2}{3}n^3 + \mathcal{O}(n^2)$$

$$\textbf{(15)} \quad \boldsymbol{A} = \boldsymbol{L}_0 \underbrace{\boldsymbol{D} \boldsymbol{L}_0^T}_{\boldsymbol{U}} \Rightarrow \boldsymbol{U}^T = \boldsymbol{L}_0 \boldsymbol{D} \Rightarrow \rho_{\texttt{chol}} = \frac{\max\left\{\left|\boldsymbol{U}^T(i,j)\right|\right\}}{\max\{\left|a_{ij}\right|\}} = \frac{\max\left\{\left|l_{ij} \cdot l_{jj}\right|\right\}}{\max\{\left|a_{ij}\right|\}} \leq \frac{\max\left\{l_{ij}^2\right\}}{\max\{a_{ii}\}} \leq 1$$

(16)
$$\mathcal{O}_{\text{chol}} = \sum_{j=1}^{n} \left[\left(1 + \sum_{k=1}^{j-1} 2 + 1 \right) + \sum_{i=j+1}^{n} \left(1 + \sum_{k=1}^{j-1} 2 + 1 \right) \right] = \sum_{j=1}^{n} \left(2j + \sum_{i=j+1}^{n} 2j \right) = 2(n+1) \sum_{j=1}^{n} j - 2 \sum_{j=1}^{n} j^{2}$$
$$= n(n+1)^{2} - \frac{n(n+1)(2n+1)}{3} = \frac{1}{3}n^{3} + \mathcal{O}(n^{2})$$

(17)
$$\mathcal{O}_{\text{thomas}} = \sum_{i=1}^{n} 6 + \sum_{i=n}^{1} 2 = 8n$$

(18)
$$\delta x = x^* - x = x^* - A^{-1}b = A^{-1}(Ax^* - b) = -A^{-1}r \Rightarrow \|\delta x\| \le \|A^{-1}\| \cdot \|r\|$$

$$(19) \quad \begin{array}{l} (A+\delta A)x^* = b+\delta b = Ax+\delta b \\ \Rightarrow A(x^*-x) = -\delta Ax^* + \delta b \\ \Rightarrow \delta x = A^{-1}(-\delta Ax^* + \delta b) \end{array} \right\} \Rightarrow \quad \begin{array}{l} \|\delta x\| \leq \|A^{-1}\| \cdot (\|\delta A\| \cdot \|x^*\| + \|\delta b\|) \\ \|\delta x\| \leq \|A^{-1}\| \cdot \|A\| \cdot \left(\frac{\|\delta A\|}{\|A\|} + \frac{\|\delta b\|}{\|A\| \cdot \|x^*\|}\right) \end{array}$$

$$(A + \delta A)x^{*} = b + \delta b \Rightarrow \overbrace{\delta x + x}^{x^{*}} = (A + \delta A)^{-1}(b + \delta b)$$

$$\Rightarrow \delta x = (A + \delta A)^{-1}(b + \delta b - (A + \delta A)x) = (A + \delta A)^{-1}(b - Ax - \delta Ax + \delta b)$$

$$= (A + \delta A)^{-1}(-\delta Ax + \delta b) \stackrel{!}{=} (I + A^{-1}\delta A)^{-1}A^{-1}(-\delta Ax + \delta b)$$

$$\Rightarrow \frac{\|\delta x\|}{\|x\|} \leq \|(I + A^{-1}\delta A)^{-1}\| \cdot \|A^{-1}\| \cdot \left(\|\delta A\| + \frac{\|\delta b\|}{\|x\|}\right) \stackrel{!}{\leq} \frac{\|A^{-1}\|}{1 - \|A^{-1}\| \cdot \|\delta A\|} \cdot \left(\|\delta A\| + \frac{\|\delta b\|}{\|x\|}\right)$$

$$= \frac{\|A^{-1}\| \cdot \|A\|}{1 - \|A^{-1}\| \cdot \|A\|} \cdot \frac{\|\delta A\|}{\|A\|} \cdot \left(\frac{\|\delta A\|}{\|A\|} + \frac{\|\delta b\|}{\|A\| \cdot \|x\|}\right)$$

$$= \frac{\kappa(A)}{1 - \kappa(A) \cdot \frac{\|\delta A\|}{\|A\|}} \cdot \left(\frac{\|\delta A\|}{\|A\|} + \frac{\|\delta b\|}{\|b\|}\right)$$

$$^{\dagger}(X + Y)^{-1} = \left(X(I + X^{-1}Y)\right)^{-1} = (I + X^{-1}Y)^{-1}X^{-1}, \quad ^{\dagger}\|(I - X)^{-1}\| \leq \frac{1}{1 - \|X\|} \quad \text{if} \quad \|X\| < 1$$

(21)
$$A(x^* + z) = Ax^* + Az = (b - r) + r = b$$

(22)
$$\begin{array}{c} PA = LU \\ Az = r \end{array} \Rightarrow PAz = LUz = Pr \Rightarrow \left\langle egin{array}{c} Ly = Pr \\ Uz = y \end{array} \right.$$

$$\begin{pmatrix}
\mathbf{A}^{T} \mathbf{A} (\mathbf{x} + \Delta \mathbf{x}) = \mathbf{A}^{T} (\mathbf{b} + \Delta \mathbf{b}) \\
\mathbf{A}^{T} \mathbf{A} \mathbf{x} = \mathbf{A}^{T} \mathbf{b}
\end{pmatrix} \Rightarrow \mathbf{A}^{T} \mathbf{A} \Delta \mathbf{x} = \mathbf{A}^{T} \Delta \mathbf{b} \Rightarrow \Delta \mathbf{x} = (\mathbf{A}^{T} \mathbf{A})^{-1} \mathbf{A}^{T} \Delta \mathbf{b}$$

$$\begin{pmatrix}
\mathbf{A}^{+} \triangleq (\mathbf{A}^{T} \mathbf{A})^{-1} \mathbf{A}^{T} \\
\kappa(\mathbf{A}) \triangleq \|\mathbf{A}\| \cdot \|\mathbf{A}^{+}\| \\
\frac{\|\mathbf{A}\mathbf{x}\|}{\|\mathbf{b}\|} \triangleq \cos \theta
\end{pmatrix} \Rightarrow \frac{\|\Delta \mathbf{x}\|}{\|\mathbf{x}\|} = \|\mathbf{A}^{+}\| \cdot \frac{\|\Delta \mathbf{b}\|}{\|\mathbf{x}\|} = \kappa(\mathbf{A}) \cdot \frac{\|\mathbf{b}\|}{\|\mathbf{A}\| \cdot \|\mathbf{x}\|} \cdot \frac{\|\Delta \mathbf{b}\|}{\|\mathbf{b}\|}$$

$$\leq \kappa(\mathbf{A}) \cdot \frac{\|\mathbf{b}\|}{\|\mathbf{A}\mathbf{x}\|} \cdot \frac{\|\Delta \mathbf{b}\|}{\|\mathbf{b}\|} = \kappa(\mathbf{A}) \cdot \frac{1}{\cos \theta} \cdot \frac{\|\Delta \mathbf{b}\|}{\|\mathbf{b}\|}$$

$$(A + E)^{T}(A + E)(x + \Delta x) = (A + E)^{T}b$$

$$\Rightarrow (A^{T}A + A^{T}E + E^{T}A + E^{T}E)(x + \Delta x) = (A + E)^{T}b$$

$$\Rightarrow \overbrace{A^{T}Ax}^{A^{T}b} + A^{T}Ex + E^{T}Ax + E^{T}Ex + A^{T}A\Delta x + A^{T}E\Delta x + E^{T}A\Delta x + E^{T}E\Delta x = \underline{A^{T}b} + E^{T}b}$$

$$A^{T}A\Delta x \approx E^{T}b - E^{T}Ax - A^{T}Ex \quad (drop 2^{nd} terms of small pertub.)$$

$$\Rightarrow E^{T}\underbrace{(b - Ax)}_{r} - A^{T}Ex$$

$$\Rightarrow \Delta x = (A^{T}A)^{-1}E^{T}r - \underbrace{(A^{T}A)^{-1}A^{T}}_{A^{T}}Ex \lessapprox \|(A^{T}A)^{-1}\| \cdot \|E\| \cdot \|r\| + \|A^{+}\| \cdot \|E\| \cdot \|x\|$$

$$\Rightarrow \frac{\|\Delta x\|}{\|x\|} \lessapprox \|(A^{T}A)^{-1}\| \cdot \|E\| \cdot \frac{\|r\|}{\|x\|} + \|A^{+}\| \cdot \|E\|$$

$$\Rightarrow \frac{\|\Delta x\|}{\|x\|} \lessapprox \|A\|^{2} \cdot \|(A^{T}A)^{-1}\| \cdot \|25\|$$

$$\Rightarrow \tan \theta \triangleq \frac{\|r\|}{\|Ax\|}$$

$$\Rightarrow (\kappa^{2}(A) \cdot \frac{\|E\|}{\|A\|} \cdot \frac{\|r\|}{\|Ax\|} + \kappa(A) \cdot \frac{\|E\|}{\|A\|}$$

$$= (\kappa^{2}(A) \cdot \tan \theta + \kappa(A)) \cdot \frac{\|E\|}{\|A\|}$$

(25)
$$\kappa^2(\mathbf{A}) = ?????$$

$$\kappa^2(\mathbf{A}) = \kappa(A^T A)$$

(26)
$$\mathcal{O}(\mathbf{A}^T \mathbf{A}) = 2m^2 n \text{ (symm.)}$$

$$\mathcal{O}_{\text{chol}}(\mathbf{A}) = \frac{1}{3}n^3 + \mathcal{O}(n^2) \text{ [16]}$$
 $\Rightarrow \mathcal{O}_{\text{chol}}(\mathbf{A}^T \mathbf{A}) = \underbrace{m^2 n}_{\text{major}} + \frac{1}{3}n^3 + \mathcal{O}(n^2)$

approx. approximate(ly), approximation

vec. vector mat. matrix

lin. linear(ly)

indp. independent(ly)
trans. transformation

eq. equation

charct. characteristic

poly. polynomial
dim. dimension(al)

spctm. spectrum

References

- [Aas71] Jan Ole Aasen. On the reduction of a symmetric matrix to tridiagonal form. BIT Numerical Mathematics, 11(3):233--242, 1971. 8
- [BK77] James R Bunch and Linda Kaufman. Some stable methods for calculating inertia and solving symmetric linear systems. *Mathematics of computation*, pages 163--179, 1977.
- [Wil61] J. H. Wilkinson. Error analysis of direct methods of matrix inversion. *J. ACM*, 8(3):281--330, July 1961. 7

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