
LIN150117

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Contents

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Theorem 0.1. *If $B \in \mathbb{R}^{n \times n}$ satisfying $\|B\| < 1$, then $I + B$ invertible and*

$$\|(I + B)^{-1}\|_2 \leq \frac{1}{1 - \|B\|}$$

Cholesky transformation

Doolittle Decomposition

Condition number

$$\mathcal{K}_2(A)^2 = \text{cond}(A^T A) \text{ if } A \text{ full of column rank}$$

$$\text{cond}(A) \geq \frac{|\lambda_1|}{|\lambda_n|} \text{ equality holds if } A \text{ is symmetric matrix}$$

$$\|A\|_2^2 = \rho(A^T A) = \|A^T A\|_2$$

Theorem 0.2. *If $\det A \neq 0$, then*

$$\min_{|A+\delta A|=0} \frac{\|\delta A\|_2}{\|A\|_2} = \frac{1}{\text{cond}(A)_2}$$

Moore-Penrose pseudoinverse

Theorem 0.3. *For the least square equation of $Ax = b$,*

$$\frac{\|\delta x\|_2}{\|x\|_2} \leq \mathcal{K}_x(A) \cdot \frac{\|A\delta x\|_2}{\|Ax\|_2}$$

Hauseholder transformation

Givens transformation

$$R_k(B) = -\ln \|B^k\|^{\frac{1}{k}}$$

$$R(B) = -\ln \rho(B)$$

Jacobian iteration

Gauss-Seidel iteration

Theorem 0.4.

Theorem 0.5. *By Steepest Descent Algorithm,*

$$\|x^k - x^*\|_A \leq \left(\frac{\lambda_n - \lambda_1}{\lambda_n + \lambda_1} \right)^k \|x^0 - x^*\|_A$$

Theorem 0.6. *In conjugated gradient method,*

$$P^{(k)} = r^{(k)} + \beta_{k-1} P^{(k-1)}$$

with

$$\beta_{k-1} = -\frac{(r^{(k)}, AP^{(k-1)})}{(P^{(k-1)}, AP^{(k-1)})}, r^{(k)} = b - Ax^{(k)}$$

And the iteration

$$x^{(k+1)} = x^{(k)} + \alpha_k P^{(k)}$$

where

$$\alpha_k = \arg \min_{\alpha \in \mathbb{R}} \varphi(x^{(k)} + \alpha P^{(k)}) = \frac{(r^{(k)}, P^{(k)})}{(P^{(k)}, AP^{(k)})}$$

This iteration satisfies

$$x^{(k)} = \arg \min_{x - x^{(0)} \in \text{Span}\{P^{(0)}, \dots, P^{(k-1)}\}} \varphi(x)$$

Theorem 0.7. $(r^{(i)}, r^{(j)}) = 0, i \neq j$

$$(AP^{(i)}, P^{(j)}) = 0, i \neq j$$

$$(r^{(j)}, P^{(i)}) = 0, i < j$$

$$\text{Span}\{r^0, \dots, r^{(k)}\} = \text{Span}\{P^{(0)}, \dots, P^{(k)}\} = \text{Span}\{r^{(0)}, Ar^{(0)}, \dots, A^k r^{(0)}\}$$

Theorem 0.8 (Arnoldi Elimination).

$$Aq_k = Q_k h_k + \beta_k q_{k+1}$$

$$h_k = Q_k^T Aq_k$$

$$\beta_k = \|Aq_k - Q_k h_k\|$$

$$q_{k+1} = \frac{Aq_k - Q_k h_k}{\beta_k}$$

Then

$$AQ_k = Q_k H_k + h_{k+1,k} q_{k+1} e_k^T$$

and

$$AQ_n = Q_n H_n, Q_n^T A Q_n = H_n$$

Theorem 0.9 (Lanczos Elimination). For A symmetric,

$$AQ_k = Q_k T_k + \beta_k q_{k+1} e_k^T$$

where T_k symmetric three triangular matrix.

Theorem 0.10 (Non-symmetric Lanczos Elimination). $\omega_i v_j = \begin{cases} 0, & i \neq j \\ 1, & i = j \end{cases}$.

$$\beta_j v_{j+1} = A v_j - \alpha_j v_j - \gamma_{j-1} v_{j-1}$$

$$\gamma_j \omega_{j+1} = A^T \omega_j - \alpha_j \omega_j - \beta_{j-1} \omega_{j-1}$$

Take inner product we obtain $\alpha_j = \omega_j^T A v_j$. And $\beta_j = \sqrt{|\eta_j|}$ for $\eta_j = \tilde{v}_{j+1}^T \tilde{\omega}_{j+1}$.

It can be derived from

$$AV_k = V_k T_k + \beta_k v_{k+1} e_k^T$$

$$A^T W_k = W_k T_k^T + \gamma_k \omega_{k+1} e_k^T$$

$$V_k^T W_k = T_k, v_{k+1}^T W_k = 0, \omega_{k+1}^T V_k = 0, \omega_{k+1}^T v_{k+1} = 1$$

$$\mathcal{K}_k(A, v_1) = \text{Span}\{v_1, \dots, v_k\}$$

$$\mathcal{K}_k(A^T, \omega_1) = \text{Span}\{\omega_1, \dots, \omega_k\}$$

Theorem 0.11 (Conjugate Gradient Method). *It follows from the fact that $(b - Ax_k) \perp$*

$\mathcal{K}_k(A, b)$ if and only if $x_k = \arg \min\{\|x - x_\|_A : x \in \mathcal{K}_k(A, b)\}$.*

Take $q_1 = \frac{b}{\|b\|_2}$. Then Lanzos method implies

$$AQ_k = Q_k T_k + \beta_k q_{k+1} e_k^T$$

For $x_k = Q_k y_k$, it is equivalent to calculate

$$T_k y_k = \beta_1$$

T_k symmetric positive definite, then

$$T_k = L_k D_k L_k^T$$

where

$$L_k = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ \gamma_1 & 1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & \cdots & \gamma_{k-1} & 1 \end{pmatrix}, D_k = \text{diag}\{\delta_1, \dots, \delta_k\}$$

Then $x_{k+1} = \tilde{P}_{k+1}z_{k+1} = x_k + \zeta_{k+1}\tilde{p}_{k+1}$ where $\tilde{P}_k = Q_k L_k^{-T}$.

Theorem 0.12 (MINRES method). $A \in \mathbb{R}^{n \times n}$ symmetric, by Lanzas elimination,

$$AQ_k = Q_{k+1}\hat{T}_k$$

where

$$T_k = \begin{pmatrix} \alpha_1 & \beta_1 & & & \\ \beta_1 & \alpha_2 & \ddots & & \\ & \ddots & \ddots & \beta_{k-1} & \\ & & \beta_{k-1} & \alpha_k & \\ & & & & \beta_k \end{pmatrix}$$

For Givens transformation $G_k G_{k-1} \cdots G_1 \hat{T}_k = \begin{pmatrix} R_k \\ 0 \end{pmatrix}$.

Then suffices to find y s.t.

$$y = \arg \min \|R_k y - t_k\|$$

Theorem 0.13. If $\varphi \in C^p$, $\varphi(x^*) = \varphi'(x^*) = \varphi''(x^*) = \cdots = \varphi^{(p-1)}(x^*) = 0$, then

$$\lim_{k \rightarrow \infty} \frac{e_{k+1}}{e_k^p} = \frac{\varphi^{(p)}(x^*)}{p!}$$

Theorem 0.14 (Steffensen iteration method). $\psi(x) = x - \frac{(\varphi(x) - x)^2}{\varphi(\varphi(x)) - 2\varphi(x) + x}$. Then fixed points of $\psi(x)$ are that of φ . If φ converges of order 1, then ψ converges for order 2. If φ converges of order $p > 1$, then ψ converges of order $2p - 1$. All under the condition that $\varphi \in C^{p+1}$.

Theorem 0.15. $f(x^*) = 0, f'(x^*) \neq 0$. $f \in C^2$ locally. Then Newton's iteration $\varphi(x) =$

$x - \frac{f(x)}{f'(x)}$ converges of order 2 locally. And

$$\lim_{k \rightarrow \infty} \frac{x_{k+1} - x^*}{(x_k - x^*)^2} = \frac{f''(x^*)}{2f'(x^*)}$$

For $f(x) = (x - x^*)^m g(x)$,

$$\varphi(x) = x - \frac{f(x)}{f'(x)} = x - \frac{(x - x^*)g(x)}{mg(x) + (x - x^*)g'(x)}$$

$$\varphi'(x) = 1 - \frac{1}{m}$$

So Newton's method converges linearly.

For $\varphi(x) = x - \frac{mf(x)}{f'(x)}$, $\varphi'(x^*) = 0$. It converges of at least two.

Or $\mu(x) = \frac{f(x)}{f'(x)}$. It has simple root x^* . Use Newton's method.

Theorem 0.16 (GeXian). $f'(x_k) \simeq \frac{f(x_k) - f(x_{k-1})}{x_k - x_{k-1}}$.

If on interval $\Delta = [x^* - \delta, x^* + \delta]$ $f'(x) \neq 0$ and $f \in C^2(\Delta)$.

$M\delta < 1$ where $M = \frac{\max_{x \in \Delta} |f''(x)|}{2 \min_{x \in \Delta} |f'(x)|}$.

Then if $x_0, x_1 \in \Delta$, it converges of order $\frac{1}{2}(1 + \sqrt{5})$.

Theorem 0.17. Iteration converges locally if $\rho(\Psi'(x^*)) = \sigma < 1$.

Theorem 0.18. Newton's method $x^{k+1} = x^k - (F'(x^k))^{-1}F(x^k)$ converges of order > 1 if $F'(x)$ invertible and continuous. If $\|F'(x) - F'(x^*)\| \leq \gamma\|x - x^*\|$, $\forall x \in S$, then $\{x^k\}$ converges of at least order 2.

Theorem 0.19. $x^{k+1} = x^k - A_k^{-1}F(x^k)$ where

$$\Delta A_k = \arg \min_{A \in Q} \|A\|_F$$

under the Frobenius norm and $Q = \{A \in \mathbb{R}^{n \times n} : L(A_k + A)p^k = q^k, p^k = x^{k+1} - x^k, q^k = F(x^{k+1}) - F(x^k)\}$.

Lemma 0.20. $A \in \mathbb{C}^{n \times n}, B \in \mathbb{C}^{p \times p}, X \in \mathbb{C}^{n \times p}$ satisfies

$$AX = XB, \text{rank}(X) = p$$

Then there exists unitary matrix $Q \in \mathbb{C}^{n \times n}$

$$Q^H A Q = T = \begin{pmatrix} T_{11} & T_{12} \\ 0 & T_{22} \end{pmatrix}$$

and $\sigma(T_{11}) = \sigma(A) \cap \sigma(B)$.

Theorem 0.21 (Schur decomposition). $A \in \mathbb{C}^{n \times n}$, then there exists unitary matrix $Q \in \mathbb{C}^{n \times n}$ s.t. $Q^H A Q = U$.

Theorem 0.22 (Real Schur decomposition). $A \in \mathbb{R}^{n \times n}$. Then there exists $Q \in \mathbb{R}^{n \times n}$ s.t.

$$Q^T A Q = \begin{pmatrix} R_{11} & R_{12} & \cdots & R_{1m} \\ & R_{22} & \cdots & R_{2m} \\ & & \ddots & \vdots \\ & & & R_{mm} \end{pmatrix}$$

Theorem 0.23. μ is an eigenvalue of $A + E \in \mathbb{C}^{n \times n}$. If $X^{-1} A X$ diagonal, then

$$\min_{\lambda \in \sigma(A)} |\lambda - \mu| \leq \|X^{-1}\|_p \cdot \|X\|_p \cdot \|E\|_p$$

Condition number w.r.t. λ of A : $\frac{1}{|y^H x|}$

Theorem 0.24. *If A, E symmetric in $\mathbb{R}^{n \times n}$. Eigenvalues of $A, E, A + E$ are*

$$\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_n$$

$$\nu_1 \geq \nu_2 \geq \cdots \geq \nu_n$$

$$\mu_1 \geq \mu_2 \geq \cdots \geq \mu_n$$

Then $\lambda_i + \nu_n \leq \mu_i \leq \lambda_i + \nu_1$.

Proof use Rayleigh quotient.

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