

T1.1 Matrices P and Q should be: $P=Q=I$

Furthermore,

$$\begin{aligned} \text{diag } U &= \text{diag}(U); \\ D &= \text{diag}(\sqrt{\text{diag}(U)}); \\ \text{all}(\text{diag } U > 0) &\text{ - should be true} \\ L &= L * D; \\ \text{---} \quad D_{\text{inv}} &= \text{diag}(1/\sqrt{\text{diag}(U)}); \\ U &= D_{\text{inv}} * U; \\ \text{norm}(L - U', 1) &\text{ - should be zero (5p.)} \end{aligned}$$

Motivation: (1) A is pos. definite iff A has Cholesky factorization
(2) Cholesky is a particular sort of LU (3p.)

T1.2 Algorithm $R_A(x)$ is called stable if

$$\frac{\|\delta x\|}{\|x\|} \text{ small} \Rightarrow \frac{\|R_A(x + \delta x) - R_A(x)\|}{\|R_A(x)\|} \text{ small}$$

T1.3 A is ^{called} normal provided that $AA^* = A^*A$.

$$\forall A \in \mathbb{C}^{n \times n} \exists \underset{\substack{\uparrow \\ \mathbb{C}^{n \times n}}}{Q} \text{ unitary, } T \in \mathbb{C}^{n \times n} \text{ upper triangular:} \\ A = QTQ^*$$

Where Q can be chosen such that the e-values of A appear in T (on the main diagonal) in any order.

T1.4 $AA^* = QTQ^* (QTQ^*)^* = QTQ^* Q T^* Q^* =$
 $= Q T T^* Q^*$

$AA^* = \dots = Q T^* T Q^*$ } $\Rightarrow TT^* = T^* T$

Inspecting this equality elementwise shows that
T is diagonal.

(derivation should be given!)

T2.1 A method is called Krylov subspace method
 if $x_k = x_0 + z_k$, $z_k \in \mathcal{K}_k(A, r_0)$

$\mathcal{K}_k(A, r_0) = \text{span}\{r_0, Ar_0, \dots, A^{k-1}r_0\}$ -

- Krylov subspace, $r_0 = b - Ax_0$

Galerkin condition: $r_k \perp \mathcal{K}_k(A, r_0)$

T2.2 $x_1 = x_0 + z_1$, $z_1 \in \mathcal{K}_1(A, r_0) = \text{span}\{r_0\}$

$\Rightarrow z_1 = \alpha r_0$

$r_1 = b - Ax_1 = b - Ax_0 - Az_1 = r_0 - \alpha Ar_0 \perp r_0$

$0 = (r_1, r_0) = (r_0, r_0) - \alpha (Ar_0, r_0) \Rightarrow \alpha = \frac{\|r_0\|^2}{(Ar_0, r_0)}$

T2.3 Let $H = \frac{1}{2}(A + A^T) = LL^T$ (Cholesky)

Two-sided preconditioner $M = M_1 M_2 = LL^T$:

$L^{-1} A L^{-T} L^T x = L^{-1} b$

$\tilde{A} = L^{-1}(H + S)L^{-T} = I + \underbrace{L^{-1}SL^{-T}}_{\text{Hermitian part of } \tilde{A}}$ because $(L^{-1}SL^{-T})^T = -L^{-1}SL^{-T}$
 skew-Herm. part of A

T2.4 $y^{k+1} - y^k = -\frac{\tau}{2} A y^{k+1} - \frac{\tau}{2} A y^k + g(t_{k+\frac{1}{2}})$

$(I + \frac{\tau}{2} A) y^{k+1} = (I - \frac{\tau}{2} A) y^k + g^{k+\frac{1}{2}}$

$(I + \frac{\tau}{2} A) (y^{k+1} - y^k) = y^k - \frac{\tau}{2} A y^k - y^k - \frac{\tau}{2} A y^k + g^{k+\frac{1}{2}}$

$(I + \frac{\tau}{2} A) x = -\tau A y^k + g^{k+\frac{1}{2}}$

T3.1 The Sylvester equation has ! solution iff

(*) $\Lambda(A) \cap \Lambda(B) = \emptyset$

E. values of A lie on the imag. axis in $\mathbb{C}$

E. values of B lie on the real axis in $\mathbb{C}$.

(*) holds iff B is nonsingular.

T3.2 Newton method: $x_{k+1} = x_k - (f''(x_k))^{-1} \nabla f(x_k)$

Secant method: $x_{k+1} = x_k - \frac{x_k - x_{k-1}}{\nabla f(x_k) - \nabla f(x_{k-1})} \nabla f(x_k)$
(For scalar problem)

Secant method in general case:

$x_{k+1} = x_k - B_k^{-1} \nabla f(x_k)$

where $B_k (x_k - x_{k-1}) = \nabla f(x_k) - \nabla f(x_{k-1})$
(quasi-Newton condition)

T3.3 (a) $M^{-1} F(x) = 0, \quad \tilde{F}(x) = M^{-1} F(x)$

(b) $x_{k+1} = x_k - M^{-1} F(x_k)$

In early iterations: $M = I$ (fixed point)

In subsequent iterations: or another fixed matrix
 $M = F'(x_k)$ (Newton method)