



Overview

- Nonsymmetric systems revisited
- Biconjugate gradient
- Preconditioning

- Arnoldi iteration: $\mathbf{A}\mathbf{Q}_n = \mathbf{Q}_{n+1}\tilde{\mathbf{H}}_n \Rightarrow \mathbf{A}\mathbf{q}_n = h_{1n}\mathbf{q}_1 + \dots + h_{n+1,n}\mathbf{q}_{n+1}$, long recurrence
- Lanczos, $\mathbf{A} = \mathbf{A}^T$: $\mathbf{A}\mathbf{Q}_n = \mathbf{Q}_{n+1}\tilde{\mathbf{T}}_n \Rightarrow \mathbf{A}\mathbf{q}_n = \beta_{n-1}\mathbf{q}_{n-1} + \alpha_n\mathbf{q}_n + \beta_n\mathbf{q}_{n+1}$, 3-term
- Approaches to obtaining a short-term recurrence algorithm for non-symmetric matrices:
 - Conjugate gradient applied to normal equations (CGN)

$$\mathbf{A}\mathbf{x} = \mathbf{b} \Rightarrow \mathbf{A}^*\mathbf{A}\mathbf{x} = \mathbf{A}^*\mathbf{b} \Leftrightarrow \mathbf{M}\mathbf{x} = \mathbf{y}, \mathbf{M} = \mathbf{A}^*\mathbf{A} = \mathbf{M}^*, \mathbf{y} = \mathbf{A}^*\mathbf{b}$$

Recall convergence estimate

$$\frac{\|\mathbf{r}_n\|_2}{\|\mathbf{r}_0\|_0} \leq 2 \left(\frac{\sqrt{\kappa_M} - 1}{\sqrt{\kappa_M} + 1} \right)^2 = 2 \left(\frac{\kappa_A - 1}{\kappa_A + 1} \right)^2, \mathcal{O}(\kappa_A) \text{ iterations}$$

- Biorthogonalization: use $\mathbf{A} = \mathbf{V}\mathbf{T}\mathbf{V}^{-1}$ (compare to Lanczos for $\mathbf{A} = \mathbf{A}^T$, $\mathbf{A} = \mathbf{Q}\mathbf{T}\mathbf{Q}^T$)

$$\begin{aligned} \mathbf{A} &= \mathbf{V}\mathbf{T}\mathbf{V}^{-1} & \mathbf{A}^* &= \mathbf{V}^{-*} \mathbf{T}^* (\mathbf{V}^{-*})^{-1} \\ (\mathbf{V}^{-*})^* \mathbf{V} &= \mathbf{W}^* \mathbf{V} = \mathbf{I} \text{ replaces } \mathbf{Q}\mathbf{Q}^* = \mathbf{I} \\ \mathbf{W} &= (\mathbf{w}_1 \ \dots \ \mathbf{w}_m), \mathbf{V} = (\mathbf{v}_1 \ \dots \ \mathbf{v}_m), \mathbf{w}_i^* \mathbf{v}_j &= \delta_{ij} \end{aligned}$$

- Full biorthogonalization: $\mathbf{W}^* \mathbf{V} = \mathbf{V}^* \mathbf{W} = \mathbf{I}$
- Partial biorthogonalization: $\mathbf{W}_n^* \mathbf{V}_n = \mathbf{V}_n^* \mathbf{W}_n = \mathbf{I}_n$, $n \leq m$

Arnoldi

$$\mathbf{A} \mathbf{Q}_n = \mathbf{Q}_{n+1} \tilde{\mathbf{H}}_n$$

Lanczos

$$\mathbf{A} \mathbf{Q}_n = \mathbf{Q}_{n+1} \tilde{\mathbf{T}}_n$$

Biorthogonalization

$$\mathbf{A} \mathbf{V}_n = \mathbf{V}_{n+1} \tilde{\mathbf{T}}_n$$

$$\mathbf{A}^* \mathbf{W}_n = \mathbf{W}_{n+1} \tilde{\mathbf{S}}_n$$

$$\mathbf{T}_n = \mathbf{S}_n^* = \mathbf{W}_n^* \mathbf{A} \mathbf{V}_n$$

$$\mathbf{V}_n, \mathbf{W}_n \in \mathbb{C}^{m \times n}$$

$$\tilde{\mathbf{S}}_n, \tilde{\mathbf{T}}_n \in \mathbb{C}^{(n+1) \times n}$$

- Theoretical framework: two Krylov spaces from arbitrary starting vectors $\mathbf{v}_1, \mathbf{w}_1$

$$\mathbf{v}_n \in \langle \mathbf{v}_1, \mathbf{A} \mathbf{v}_1, \dots, \mathbf{A}^{n-1} \mathbf{v}_1 \rangle, \mathbf{w}_n \in \langle \mathbf{w}_1, \mathbf{A}^* \mathbf{w}_1, \dots, (\mathbf{A}^*)^{n-1} \mathbf{w}_1 \rangle$$

- Applications:

- Eigenvalues: Ritz values, i.e., eigenvalues of \mathbf{T}_n can rapidly converge to eigenvalues of \mathbf{A}
- Biconjugate gradient to solve $\mathbf{A} \mathbf{x} = \mathbf{b}$

- GMRES:

$$\begin{aligned}\boldsymbol{x} \in \mathcal{K}_n &= \mathcal{R}(\boldsymbol{K}_n), & \boldsymbol{K}_n &= (\boldsymbol{b} \ \boldsymbol{Ab} \ \dots \ \boldsymbol{A}^{n-1}\boldsymbol{b}) \\ \boldsymbol{r}_n \perp \mathcal{A}\mathcal{K}_n &= \mathcal{R}(\boldsymbol{A}\boldsymbol{K}_n)\end{aligned}$$

- BCG:

$$\begin{aligned}\boldsymbol{x} \in \mathcal{K}_n &= \mathcal{R}(\boldsymbol{K}_n), & \boldsymbol{K}_n &= (\boldsymbol{b} \ \boldsymbol{Ab} \ \dots \ \boldsymbol{A}^{n-1}\boldsymbol{b}) \\ \boldsymbol{r}_n \perp \mathcal{L}_n &= \mathcal{R}(\boldsymbol{L}_n), & \boldsymbol{L}_n &= (\boldsymbol{w}_1 \ \boldsymbol{A}^*\boldsymbol{w}_1 \ \dots \ (\boldsymbol{A}^*)^{n-1}\boldsymbol{w}_1)\end{aligned}$$

Algorithm

$\boldsymbol{x}_0 = \mathbf{0}$, $\boldsymbol{p}_0 = \boldsymbol{r}_0 = \boldsymbol{b}$, $\boldsymbol{q}_0 = \boldsymbol{s}_0$ arbitrary

for $n = 1, 2, 3, \dots$

$$\alpha_n = (\boldsymbol{s}_{n-1}^* \boldsymbol{r}_{n-1}) / (\boldsymbol{q}_{n-1}^* \boldsymbol{A} \boldsymbol{p}_{n-1})$$

$$\boldsymbol{x}_n = \boldsymbol{x}_{n-1} + \alpha_n \boldsymbol{p}_{n-1}$$

$$\boldsymbol{r}_n = \boldsymbol{r}_{n-1} - \alpha_n \boldsymbol{A} \boldsymbol{p}_{n-1}$$

$$\boldsymbol{s}_n = \boldsymbol{s}_{n-1} - \bar{\alpha}_n \boldsymbol{A}^* \boldsymbol{q}_{n-1}$$

$$\beta_n = (\boldsymbol{s}_n^* \boldsymbol{r}_n) / (\boldsymbol{s}_{n-1}^* \boldsymbol{r}_{n-1})$$

$$\boldsymbol{p}_n = \boldsymbol{r}_n + \beta_n \boldsymbol{p}_{n-1}$$

$$\boldsymbol{q}_n = \boldsymbol{s}_n + \bar{\beta}_n \boldsymbol{q}_{n-1}$$



- Convergence of Krylov methods on $\mathbf{A}\mathbf{x} = \mathbf{b}$ depends on spectrum $\Lambda(\mathbf{A})$
- Preconditioning idea: modify the spectrum

$$\mathbf{A}\mathbf{x} = \mathbf{b}, \mathbf{M} \text{ non-singular} \Rightarrow \mathbf{M}^{-1}\mathbf{A}\mathbf{x} = \mathbf{M}^{-1}\mathbf{b}$$

with operator \mathbf{M}^{-1} denoting solution of $\mathbf{M}\mathbf{y} = \mathbf{c}$

- Choice of \mathbf{M}
 - Ideally, $\mathbf{M}^{-1} = \mathbf{A}^{-1} \Rightarrow \mathbf{I}\mathbf{x} = \mathbf{M}^{-1}\mathbf{b}$
 - In practice choose $\mathbf{M}^{-1} \cong \mathbf{A}^{-1}$:
 - partial \mathbf{LU} factorization
 - coarse grid approximation (multigrid)
 - low-order discretization
 - operator splitting
 - dimensional splitting