

Polynomial Iterative Methods

Simple iteration

$$x^{(k)} = (M^{-1}N)x^{(k-1)} + \hat{b} \quad , \quad \hat{b} = M^{-1}b$$

$$\text{and} \quad x = (M^{-1}N)x + \hat{b}$$

$$\Rightarrow x - x^{(k)} = (M^{-1}N)(x - x^{(k-1)})$$

$$\Rightarrow x - x^{(k)} = (M^{-1}N)^k (x - x^{(0)}) = S^k (x - x^{(0)})$$

if $S = M^{-1}N$. ie.

$$x - x^{(k)} = p_k(S)(x - x^{(0)}) = S^k (x - x^{(0)}) \quad , \quad p_k(z) = z^k$$

Now if

$$x - x^{(0)} = \sum_{i=1}^n \alpha_i v_i, \quad S v_i = \lambda_i v_i$$

$$x - y^{(k)} = \sum_{i=1}^n \alpha_i p_k(S) v_i = \sum_{i=1}^n \alpha_i p_k(\lambda_i) v_i$$

Idea: $x - y^{(k)}$ should be small if $p_k(\lambda_i)$ is small

If S is symmetric we can say more
 (since S orthogonally diagonalisable)

$$\Rightarrow S = U\Lambda U^T, \quad UU^T = I$$

↑ diag Matrix of eigenvalues

$$\Rightarrow S^2 = U\Lambda U^T U\Lambda U^T = U\Lambda^2 U^T, \dots, S^k = U\Lambda^k U^T$$

$$\Rightarrow p(S) = Up(\Lambda)U^T \quad \text{any polynomial } p$$

$$\Rightarrow \|p(S)\|_2 = \|Up(\Lambda)U^T\|_2 = \|p(\Lambda)\|_2$$

$$= \left\| \begin{bmatrix} p(\lambda_1) & & & O \\ & p(\lambda_2) & & \\ & & \ddots & \\ O & & & p(\lambda_n) \end{bmatrix} \right\|_2$$

$$= \max_i |p(\lambda_i)|$$

So for polynomial iteration $x - y^{(k)} = p_k(S)(x - x^0)$

$$\|x - y^{(k)}\|_2 \leq \|p_k(S)\|_2 \|x - x^{(0)}\|_2 = \max_i |p_k(\lambda_i)| \|x - x^{(0)}\|_2$$

So desire $p_k \in \Pi_k$ is small at eigenvalues with $p_k(1) = 1$.

Notes:

- if $\lambda_i = 1$ for some i
 $\Rightarrow Sv_i = v_i \Leftrightarrow Mv_i = Nv_i \Leftrightarrow Av_i = 0$ i.e. A singular.
- If only k distinct eigenvalues of S : choose p_k to have these as roots.

For such a p_k , $\|x - y^{(k)}\|_2 = 0$ i.e. termination after k steps!

Candidates for $\{p_k\}$? : Chebyshev polynomials

Suppose $\lambda_i(S) \in [a, b]$, $1 \notin [a, b]$ then

$$\begin{aligned} \|x - y^{(k)}\|_2 &\leq \max_i |p_k(\lambda_i)| \|x - x^{(0)}\|_2 \\ &\leq \max_{t \in [a, b]} |p_k(t)| \|x - x^{(0)}\|_2 \end{aligned}$$

and the polynomials which

$$p \in \Pi_k, p(1) = 1 \quad \text{minimise} \quad \max_{t \in [a, b]} |p(t)|$$

are shifted and scaled Chebyshev polynomials

Chebyshev polynomials are defined on $[-1, 1]$ by $T_0(t) = 1$ and for $m = 1, 2, \dots$ by

$$T_m(t) = \begin{cases} \frac{1}{2^{m-1}} \cos m\theta & (0 \leq \theta \leq \pi) \\ \quad \text{where } t = \cos \theta & -1 \leq t \leq 1 \\ \\ \frac{1}{2^{m-1}} \cosh m\theta & \\ \quad \text{where } t = \cosh \theta & t \geq 1 \\ \\ (-1)^m T_m(-t) & t \leq -1 \end{cases}$$

$$T_0 = 1, \quad T_1 = t,$$

$$T_2 = \frac{1}{2} \cos 2\theta = \frac{1}{2} (2 \cos^2 \theta - 1) = t^2 - \frac{1}{2}, \quad \dots$$

In general since

$$\cos(m + 1) \theta = \cos m\theta \cos \theta - \sin m\theta \sin \theta$$

$$\cos(m - 1) \theta = \cos m\theta \cos \theta + \sin m\theta \sin \theta$$

we have

$$\cos(m + 1) \theta + \cos(m - 1) \theta = 2 \cos m\theta \cos \theta$$

$$\text{i.e. } 2^m T_{m+1}(t) + 2^{m-2} T_{m-1}(t) = 2 \cdot 2^{m-1} T_m(t) t$$

or

$$T_{m+1}(t) = t T_m(t) - \frac{1}{4} T_{m-1}(t), \quad m = 2, 3, \dots \quad (\star)$$

so

$$T_3(t) = t(t^2 - \frac{1}{2}) - \frac{1}{4}t = t^3 - \frac{3}{4}t, \quad \text{etc.}$$

If $\lambda_i(S) \in [a, b]$, $1 \notin [a, b]$, need to shift using linear map

$$\begin{array}{ccc} [a, b] & \mapsto & [-1, 1] \\ \in & & \in \\ r & & t \end{array} \quad : \quad t = \frac{2r - a - b}{b - a}$$

$$\Rightarrow \hat{T}_k(r) = T_k\left(\frac{2r - a - b}{b - a}\right) / T_k\left(\frac{2 - a - b}{b - a}\right)$$

satisfies $\hat{T}_k(1) = 1$ and minimises

$$\max_{r \in [a, b]} |p(r)|$$

over all polynomials of degree $\leq k$.

Using $p_k = \hat{T}_k$ is called the
Chebyshev semi-iterative method.

Remarks:

1. need estimates $a \lesssim \lambda_{\min}(S)$ and $b \gtrsim \lambda_{\max}(S)$ in order to construct \hat{T}_k 's on a reasonable interval
2. can use the 3-term recurrence (\star) to make the algorithm more efficient than using the coefficients $\beta_e^{(k)}$ of the polynomials $T_k(z)$ explicitly (see exercise)
3. Convergence: we have

$$\|x - y^{(k)}\|_2 \leq \max_{r \in [a, b]} |\hat{T}_k(r)| \|x - x^{(0)}\|$$

if $\lambda_i \in [a, b]$, $1 \notin [a, b]$

$$\begin{aligned} \max_{r \in [a, b]} |\hat{T}_k(r)| &= |\hat{T}_k(a)| = |\hat{T}_k(b)| \\ &= \frac{|T_k(1)|}{|T_k(\frac{2-a-b}{b-a})|} \end{aligned}$$

as max error always attained at end points.

