

Lecture Note 3

Chebyshev Acceleration

March 23, 2010

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Chebyshev Acceleration Method

- Example of Large Dominance Ratio Cases (Causing Slow Convergence of Power Method)

– Consider an eigenvalue problem in 1-D particle diffusion

$$-D \frac{d^2 \phi}{dx^2} + \Sigma \phi = \lambda \nu \Sigma_f \phi, \quad x \in [0, a], \quad \phi(0) = 0, \quad \phi(a) = 0$$

– Discretization would lead to $A\phi = \lambda\phi$ → Eigenvalue of the diff. eqn. being the same as that of matrix equation

– Rearrange after dividing by D, $\frac{d^2 \phi}{dx^2} + \frac{\lambda \nu \Sigma_f - \Sigma}{D} \phi = 0$

– Let $B^2 = \frac{\lambda \nu \Sigma_f - \Sigma}{D} \rightarrow \frac{d^2 \phi}{dx^2} + B^2 \phi = 0 \rightarrow 0$ Flux Boundary Condition $\rightarrow B_n = \frac{n\pi}{a}$

– Eigenvalue $\lambda_n = \frac{\Sigma + DB_n^2}{\nu \Sigma_f} = \frac{\Sigma + \frac{n^2 \pi^2}{a^2}}{\nu \Sigma_f}$

– As $a \rightarrow \infty$, $\sigma \rightarrow 1.0$ (or $\Sigma \uparrow$ or $D \downarrow$)

$$\blacksquare \text{ Dominance Ratio } \sigma = \frac{\lambda_2}{\lambda_1} = \frac{\frac{1}{\Sigma + D \frac{\pi^2}{a^2}}}{\frac{1}{\Sigma + D \frac{4\pi^2}{a^2}}}$$

for smallest eigenvalue

- Diffusion problems for large domain have large dominance ratio

→ Slow convergence of power method

Properties of Chebyshev Polynomial (1/2)

- Chebyshev polynomial $T_m(x) = \cos(m \cos^{-1} x)$
 $= \cos(m\theta)$
 $\theta = \cos^{-1} x \quad x = \cos \theta$
 $x \in [-1,1] \Leftrightarrow \theta \in [-\pi, 0]$

- Examples of Chebyshev polynomial

$$T_0(x) = \cos(0) = 1$$

$$T_1(x) = \cos(\cos^{-1} x) = x$$

$$T_2(x) = \cos(2 \cos^{-1} x) = ? \quad T_2(x) = 2xT_1(x) - T_0(x) = 2x^2 - 1$$

$$T_3(x) = \cos(3 \cos^{-1} x) = ? \quad T_3(x) = 2xT_2(x) - T_1(x) = 2x(2x^2 - 1) - x = 4x^3 - 3x$$

- Recurrence Relation

$$+ \left\{ \begin{array}{l} T_{m+1}(x) = \cos((m+1)\theta) = \cos m\theta \cos \theta - \sin m\theta \sin \theta \\ T_{m-1}(x) = \cos((m-1)\theta) = \cos m\theta \cos \theta + \sin m\theta \sin \theta \end{array} \right.$$

$$T_{m+1}(x) + T_{m-1}(x) = 2 \cos m\theta \cos \theta = 2xT_m(x)$$

$$\therefore T_{m+1}(x) = 2xT_m(x) - T_{m-1}(x)$$

Properties of Chebyshev Polynomial (2/2)

- m Roots in $[-1,1]$

$$T_m(x) = \cos(m\theta)$$

$$m\theta_{mk} = -\left(\frac{\pi}{2} + k\pi\right) \text{ for } k = 0..(m-1)$$

- Maximum Absolute Value = 1.0

$$x_{mk} = \cos\theta_{mk} = \cos\left(-\left(\frac{1}{2} + k\right)\frac{\pi}{m}\right)$$

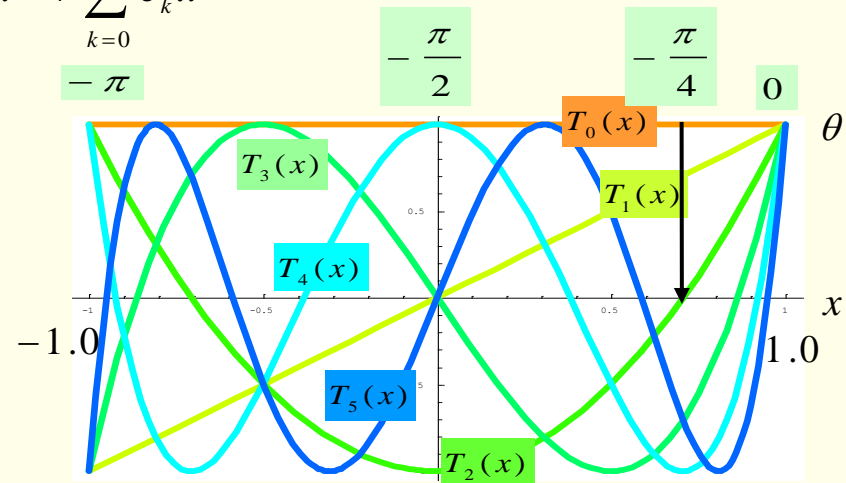
- $(m+1)$ maximum values of 1.0 for $|T_m(x)|$ with alternating sign

- Coefficient of the Highest order term : 2^{m-1}

→ Normalized Chebyshev $\phi_m^T(x) = \frac{1}{2^{m-1}}T_m(x) = x^m + \sum_{k=0}^{m-1} c_k x^k$

- Orthogonality

$$\int_{-1}^1 \frac{T_m(x)T_n(x)}{\sqrt{1-x^2}} dx = 0 \text{ for } m \neq n$$



Significance of Chebyshev Polynomial (1/2)

- Among the various normalized polynomials of order m (coefficient of the m -th order term being 1.0),

normalized Chebyshev Polynomial has the **smallest maximum** in $[-1,1]$.

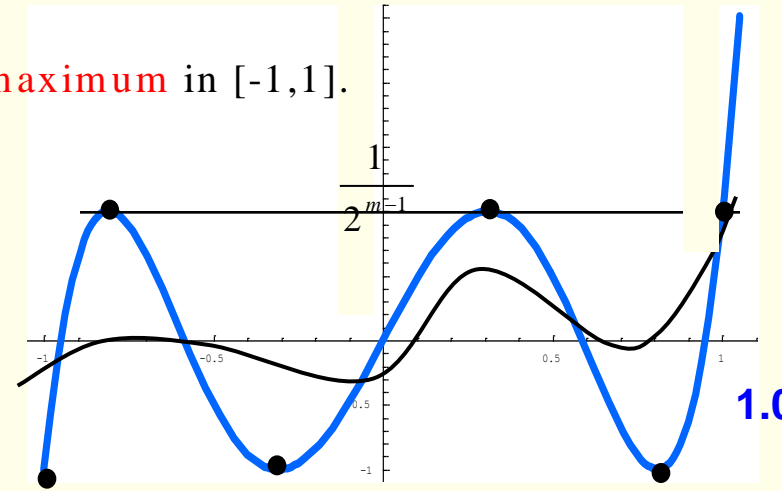
And the maximum is $\frac{1}{2^{m-1}}$

- Proof

- Assume there is a polynomial of order m

$$\min_{-1 \leq x \leq 1} (\max |p_m(x)|) = \|p_m(x)\|_{\infty} < \frac{1}{2^{m-1}}$$

- Define $E_m(x) = \phi_m^T(x) - p_m(x)$ which becomes an $(m-1)$ th order function (x^m cancelled)
- Among the $(m+1)$ maximal points, $E_m(x)$ is **positive** at the odd numbered points from the right ($x = 1$) whereas **negative** at even numbered points ← Assumption.
- This means $E_m(x)$ has m zeros, or m -th order polynomial which is a contradiction. (not $m - 1$ th order) → Chebyshev has the smallest maximum.



Significance of Chebyshev Polynomial (2/2)

- Other interpretation: Among the various polynomials of order m

passing through $(1+a, b)$ ($a, b > 0$),

$$x > 1, \quad T_m(x) = \cosh(m \cosh^{-1} x),$$

Chebyshev Polynomial has the smallest maxima in $[-1, 1]$.

And the maxima is 1.0.

- Proof

– Under the same assumption as the above,

$E(x)$ has m zeros in $[-1, 1]$

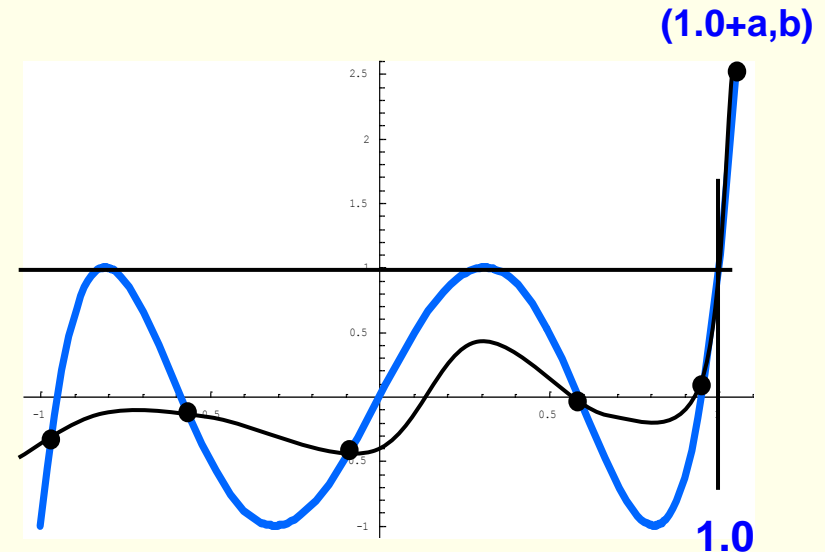
since there are $m+1$ alternating maxima,

and one more zero at $1+a$

leading to a total $m+1$ zeros.

→ $(m+1)$ th order polynomial

→ Contradiction



- Corollary: Among the m -th order polynomials passing through $(1+a, 1.0)$,

$$\tilde{T}_m(x) = \frac{T_m(x)}{T_m(1+a)}$$

has the minimax in $[-1, 1]$.

Chebyshev Acceleration Method

- Single Parameter Method

- Extrapolation of eigenvector using the current estimate by power method and the previous iterate

$$x^{(k)} = \omega^{(k)} x_{Pow}^{(k)} + (1 - \omega^{(k)}) x^{(k-1)} = \omega^{(k)} \frac{1}{\lambda^{(k-1)}} Ax^{(k-1)} + (1 - \omega^{(k)}) x^{(k-1)}$$

- The extrapolation parameter is the single parameter and it is **iteration dependent**

- Two Parameter Method

- Extrapolation using two previous iterates

$$x^{(k)} = \alpha^{(k)} x_{Pow}^{(k)} + (1 - \alpha^{(k)} + \beta^{(k)}) x^{(k-1)} - \beta^{(k)} x^{(k-2)}$$

Two Parameter Chebyshev Acceleration (1/4)

- Drawback's of Single Parameter Method

- The polynomial order (K) is preset
- The extrapolation parameter becomes very large for large K
→ too much extrapolation

- Two Parameter Method

$$\begin{aligned}x^{(k)} &= \alpha^{(k)} x_{Pow}^{(k)} + (1 - \alpha^{(k)} + \beta^{(k)})x^{(k-1)} - \beta^{(k)} x^{(k-2)} \\ &= \alpha^{(k)} \frac{1}{\lambda^{(k-1)}} Ax^{(k-1)} + (1 - \alpha^{(k)} + \beta^{(k)})x^{(k-1)} - \beta^{(k)} x^{(k-2)}\end{aligned}$$

For $x^{(0)} = c_1 u_1 + c_2 u_2 + \dots + c_n u_n$ and $\beta^{(1)} = 0$

$$\begin{aligned}x^{(1)} &= \alpha^{(1)} \frac{1}{\lambda^{(0)}} A \sum_{i=1}^n c_i u_i + (1 - \alpha^{(1)}) \sum_{i=1}^n c_i u_i \\ &= \sum_{i=1}^n c_i \left(\alpha^{(1)} \frac{\lambda_i}{\lambda^{(0)}} + (1 - \alpha^{(1)}) \right) u_i = \sum_{i=1}^n c_i p^{(1)}(\lambda_i) u_i \quad \text{with a first order polynomial } p^{(1)}(\gamma)\end{aligned}$$

▷ Each iteration will increase the order of **polynomial of eigenvalue by 1**,

which leads to a k-th order polynomial at the k-th step → Let $x^{(k)} = \sum_{i=1}^n c_i p^{(k)}(\lambda_i) u_i$

Two Parameter Chebyshev Acceleration (2/4)

Define $\gamma_i = 2 \frac{\lambda_i}{\lambda_2} - 1$

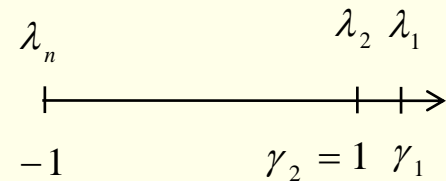
so that $\lambda_i = \frac{\gamma_i + 1}{2} \lambda_2$.

Normally, $\lambda_2 \gg \lambda_n \sim 0$

$\lambda_i : \lambda_n \rightarrow \lambda_2$

$\gamma_i : -1 \rightarrow 1$

$\gamma_1 = 2 \frac{\lambda_1}{\lambda_2} - 1 = \frac{2}{\sigma} - 1 > 1$



Then $x^{(k)} = \sum_{i=1}^n c_i p^{(k)}(\lambda_i) u_i = \sum_{i=1}^n c_i \eta^{(k)}(\gamma_i) u_i$

$x^{(k)} = \eta^{(k)}(\gamma_1) \left(c_1 u_1 + \sum_{i=2}^n c_i u_i \frac{\eta^{(k)}(\gamma_i)}{\eta^{(k)}(\gamma_1)} \right)$

can be minimum if $\eta^{(k)}(\gamma)$ is a Chebyshev polynomial of order k

But note that $\eta^{(k)}(\gamma_1)$ can increase indefinitely as k increases if it is an ordinary Chebyshev.

Thus consider a constant multiple (c_k) of Chebyshev polynomial to make $\eta^{(k)}(\gamma_1)$ constant.

$\frac{c_k T_k(\gamma_i)}{c_k T_k(\gamma_1)} = \tilde{T}_k(\gamma_i)$ still minimizes the error term.

$\eta^{(k)}(\gamma_1) = c_k T_k(\gamma_1) = 1 \rightarrow c_k = \frac{1}{T_k(\gamma_1)}$

$\eta^{(k)}(\gamma) = \frac{T_k(\gamma)}{T_k(\gamma_1)} = \tilde{T}_k(\gamma)$

$\eta^{(k)}(\gamma_1) = 1$ **desired**

Two Parameter Chebyshev Acceleration (3/4)

- Continued Derivation

$$x^{(k)} = \sum_{i=1}^n c_i u_i \left[\left(\alpha^{(k)} \frac{\lambda_i}{\lambda^{(k-1)}} + 1 - \alpha^{(k)} + \beta^{(k)} \right) \eta^{(k-1)}(\gamma_i) - \beta^{(k)} \eta^{(k-2)}(\gamma_i) \right] \leftarrow \lambda_i = \frac{1 + \gamma_i}{2} \lambda_2$$

$$= \sum_{i=1}^n c_i u_i \left[\left(\alpha^{(k)} \frac{\lambda_2}{\lambda^{(k-1)}} \frac{1 + \gamma_i}{2} + 1 - \alpha^{(k)} + \beta^{(k)} \right) \eta^{(k-1)}(\gamma_i) - \beta^{(k)} \eta^{(k-2)}(\gamma_i) \right] = \sum_{i=1}^n c_i u_i \eta^{(k)}(\gamma_i)$$

$$\eta^{(k)}(\gamma) = \left(\alpha^{(k)} \sigma \frac{1 + \gamma}{2} + 1 - \alpha^{(k)} + \beta^{(k)} \right) \eta^{(k-1)}(\gamma) - \beta^{(k)} \eta^{(k-2)}(\gamma) \leftarrow \frac{\lambda_2}{\lambda^{(k-1)}} \approx \frac{\lambda_2}{\lambda_1} = \sigma$$

- Choose $\alpha^{(k)}$ and $\beta^{(k)}$ such that the above recurrence relation be the same as $\tilde{T}_k(\gamma)$

Two Parameter Chebyshev Acceleration (4/4)

- Chebyshev Recurrence Relation for the normalized one

$$T_k(\gamma) = 2\gamma T_{k-1}(\gamma) - T_{k-2}(\gamma)$$

$$\tilde{T}_k(\gamma) = 2\gamma \frac{T_{k-1}(\gamma)}{T_k(\gamma_1)} - \frac{T_{k-2}(\gamma)}{T_k(\gamma_1)} = 2\gamma \frac{T_{k-1}(\gamma_1)}{T_k(\gamma_1)} \frac{T_{k-1}(\gamma)}{T_{k-1}(\gamma_1)} - \frac{T_{k-2}(\gamma_1)}{T_k(\gamma_1)} \frac{T_{k-2}(\gamma)}{T_{k-2}(\gamma_1)}$$

$$= 2\gamma \frac{T_{k-1}(\gamma_1)}{T_k(\gamma_1)} \tilde{T}_{k-1}(\gamma) - \frac{T_{k-2}(\gamma_1)}{T_k(\gamma_1)} \tilde{T}_{k-2}(\gamma)$$

$$\alpha^{(k)} \sigma \frac{1}{2} + 1 - \alpha^{(k)} + \beta^{(k)} = 0$$

$$\rightarrow \beta^{(k)} = \left(1 - \frac{\sigma}{2}\right) \alpha^{(k)} - 1$$

Compare this with

$$\eta^{(k)}(\gamma) = \left(\alpha^{(k)} \sigma \frac{1+\gamma}{2} + 1 - \alpha^{(k)} + \beta^{(k)} \right) \eta^{(k-1)}(\gamma) - \beta^{(k)} \eta^{(k-2)}(\gamma)$$

$$\rightarrow \begin{cases} \alpha^{(k)} \sigma \frac{1+\gamma}{2} + 1 - \alpha^{(k)} + \beta^{(k)} = 2\gamma \frac{T_{k-1}(\gamma_1)}{T_k(\gamma_1)} \\ \beta^{(k)} = \frac{T_{k-2}(\gamma_1)}{T_k(\gamma_1)} \end{cases} \quad \text{Coef. of } \gamma \rightarrow \alpha^{(k)} = \frac{4}{\sigma} \frac{T_{k-1}(\gamma_1)}{T_k(\gamma_1)} \quad \begin{cases} \gamma_1 = \frac{2}{\sigma} - 1 \\ T_k(\gamma_1) = 2\gamma_1 T_{k-1}(\gamma_1) - T_{k-2}(\gamma_1) \end{cases}$$

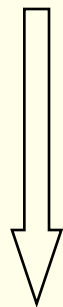
Equality of the constant term holds

Practical Estimation of σ

- Dominance Ratio σ

- σ is important because σ is used for calculating extrapolation parameters

$$\sigma = \frac{\lambda_2}{\lambda_1} = \frac{\|x^{(l)} - x^*\|}{\|x^{(l-1)} - x^*\|} \quad \leftrightarrow \quad e^{(l)} = \sigma e^{(l-1)}$$



$$\begin{aligned} & \left\{ \begin{array}{l} x^{(l)} - x^* = \sigma (x^{(l-1)} - x^*) \\ x^{(l-1)} - x^* = \sigma (x^{(l-2)} - x^*) \end{array} \right. \\ & \underline{\hspace{10em}} \\ & x^{(l)} - x^{(l-1)} = \sigma (x^{(l-1)} - x^{(l-2)}) \end{aligned}$$

$$\tilde{e}^{(l)} \equiv x^{(l)} - x^{(l-1)} : \text{pseudo error}$$

$$\sigma = \frac{\|e^{(l)}\|}{\|e^{(l-1)}\|} = \frac{\|\tilde{e}^{(l)}\|}{\|\tilde{e}^{(l-1)}\|}$$

Not valid

if extrapolation performed

Error Reduction at l-th step of chebyshev (1/4)

- Theoretical Error Reduction Factor

– let $x^{(0)} = \sum_{i=1}^N c_i u_i$

$\eta^{(l)}(\gamma)$: l -th order normalized
chebyshev polynomial

$$x^{(l)} = \sum_{i=1}^N \left[\eta^{(l)}(\gamma_i) c_i u_i \right]$$

x^* : Exact solution

$$e^{(l)} = x^{(l)} - x^*$$

$$= \sum_{i=1}^N \left[\eta^{(l)}(\gamma_i) c_i u_i \right] - x^*$$

$$= \left[c_1 u_1 + \eta^{(l)}(\gamma_2) c_2 u_2 + O(\gamma_3) \right] - x^* \quad \leftarrow \eta^{(l)}(\gamma_1) = 1$$

$$= \eta^{(l)}(1) c_2 u_2 + O(\gamma_3) \quad \leftarrow \text{Let } x^* = c_1 u_1$$

$$\zeta_l^* = \frac{\|e^{(l)}\|}{\|e^{(0)}\|} \approx \frac{\eta^{(l)}(1) \|c_2 u_2\|}{\|c_2 u_2\|} = \eta^{(l)}(1) = \frac{1}{T_l(\gamma_1)}$$

$$\gamma_1 = \frac{2}{\sigma} - 1 \text{ with exact } \sigma$$

Error Reduction at l-th step of chebyshev (2/4)

- Error Reduction in Practice

$$x^{(l-1)} = \sum_{i=1}^N \left[\eta^{(l-1)}(\gamma_i) c_i u_i \right] = c_1 u_1 + \eta^{(l-1)}(1) c_2 u_2 + \dots$$

$$x_{Pow}^{(l)} = A \frac{x^{(l-1)}}{\lambda_1}$$

$$\left(\because \eta^{(l-1)}(\gamma_1) = 1, \gamma_2 = 1, \frac{\lambda_2}{\lambda_1} = \sigma \right)$$

$$= \sum_{i=1}^N \left[\frac{\lambda_i}{\lambda_1} \eta^{(l-1)}(\gamma_i) c_i u_i \right]$$

$$= \frac{\lambda_1}{\lambda_1} \eta^{(l-1)}(\gamma_1) c_1 u_1 + \frac{\lambda_2}{\lambda_1} \eta^{(l-1)}(\gamma_2) c_2 u_2 + \dots$$

$$= c_1 u_1 + \sigma \eta^{(l-1)}(1) c_2 u_2 + \dots$$

- Pseudo Error of the l-th Power Estimate

$$\tilde{e}_{Pow}^{(l)} = x_{Pow}^{(l)} - x^{(l-1)}$$

$$= \left[c_1 u_1 + \sigma \eta^{(l-1)}(1) c_2 u_2 + \dots \right] - \left[c_1 u_1 + \eta^{(l-1)}(1) c_2 u_2 + \dots \right]$$

$$\approx (\sigma - 1) \eta^{(l-1)}(1) c_2 u_2$$

Error Reduction at l-th step of chebyshev (3/4)

- Error Reduction factor (practically – Conti.)

$$\tilde{e}_{Pow}^{(l)} = x_{Pow}^{(l)} - x^{(l-1)} \approx (\sigma - 1) \eta^{(l-1)}(1) c_2 u_2$$

$$\tilde{e}_{Pow}^{(1)} = x_{Pow}^{(1)} - x^{(0)} \approx (\sigma - 1) \eta^{(0)}(1) c_2 u_2$$

$$\eta^{(0)}(1) = 1$$

$$\zeta_l \equiv \frac{\|\tilde{e}_{Pow}^{(l)}\|}{\|\tilde{e}_{Pow}^{(1)}\|} = \frac{\|x_{Pow}^{(l)} - x^{(l-1)}\|}{\|x_{Pow}^{(1)} - x^{(0)}\|} = \frac{(\sigma - 1) \eta^{(l-1)}(1) \|c_2 u_2\|}{(\sigma - 1) \eta^{(0)}(1) \|c_2 u_2\|} = \eta^{(l-1)}(1) = \tilde{T}_{l-1}(1) = \frac{T_{l-1}(1)}{T_{l-1}(\gamma_1)} = \frac{1}{T_{l-1}(\gamma_1)}$$

$= \zeta_{l-1}^*$ → can be obtained during iteration without knowing σ

- * Error reduction in practice obtained after power iteration at the l -th step can be the theoretical error reduction for $(l-1)$ th step if all the parameters used (σ) are correct.

But in reality $\zeta_l < \zeta_{l-1}^*$ because faster decay of higher modes in early stage where higher modes are present

Error Reduction at l-th step of chebyshev (4/4)

- New dominance ratio (σ') from chebyshev acceleration

Let $\zeta_l = \tilde{T}_{l-1}(\gamma'_2) = \frac{T_{l-1}(\gamma'_2)}{T_{l-1}(\gamma_1)} \leftarrow$ Error reduction factor practically obtained is a value corresponding to a $\gamma > 1$

$$T_{l-1}(\gamma'_2) = \zeta_l T_{l-1}(\gamma_1) = \frac{\zeta_l}{\zeta_{l-1}^*} = \xi$$

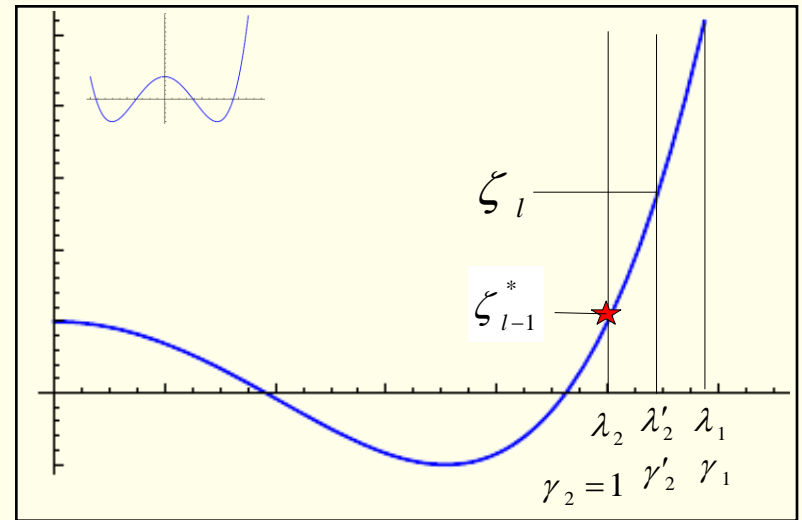
$$\cosh[(l-1)\cosh \gamma'_2] = \xi$$

$$\gamma'_2 = \cosh\left(\frac{\cosh^{-1} \xi}{l-1}\right)$$

$$2 \frac{\lambda'_2}{\lambda_2} - 1 = \gamma'_2$$

$$\lambda'_2 = \lambda_2 \frac{1 + \gamma'_2}{2}$$

$$\sigma' = \sigma \frac{1 + \gamma'_2}{2} \quad (\text{New dominance ratio})$$



smaller $\sigma \rightarrow$ larger $\gamma_1 \rightarrow$ smaller ζ_{l-1}^*

⊗ means that previously used σ was too low.

Chebyshev Acceleration Logic (1/3)

- Chebyshev Acceleration Logic

1. Perform power iteration for first n_0 iterations ($n_0 \geq 3$) and estimate σ

2. Start chebyshev acceleration at $(n_0 + 1)$ th step

① Determine $x_{pow}^{(n_0+1)} = A\hat{x}^{(n_0+1)} = \frac{1}{\lambda^{(n_0)}} Ax^{(n_0)}$

② Determine $\lambda^{(n_0+1)} = \lambda^{(n_0)} \frac{\langle x_{pow}^{(n_0+1)}, x_{pow}^{(n_0+1)} \rangle}{\langle x_{pow}^{(n_0+1)}, x^{(n_0)} \rangle}$

③ Determine pseudo error $\|\tilde{e}^{(n_0+1)}\| = \|x_{pow}^{(n_0+1)} - x^{(n_0)}\|$

④ Determine extrapolation parameter $\alpha = \frac{2}{2 - \sigma}$, $\beta = 0 \leftarrow \alpha\sigma \frac{\gamma+1}{2} + 1 - \alpha = \frac{\gamma}{\gamma_1}$

⑤ Perform extrapolation $x^{(n_0+1)} = \alpha x_{pow}^{(n_0+1)} + (1 - \alpha)x^{(n_0)}$

Chebyshev Acceleration Logic (2/3)

3. Continue chebyshev acceleration at least two more steps, $l = n_0 + 3$, $m = l - n_0$ (chebyshev order)

① Determine $x_{pow}^{(l)} = A\hat{x}^{(l)} = \frac{1}{\lambda^{(l-1)}} Ax^{(l-1)}$

② Determine $\lambda^{(l)} = \lambda^{(l-1)} \frac{\langle x_{pow}^{(l)}, x_{pow}^{(l)} \rangle}{\langle x_{pow}^{(l)}, x^{(l-1)} \rangle}$

③ Determine pseudo error $\|\tilde{e}^{(m)}\| = \|x_{pow}^{(l)} - x^{(l-1)}\|$

④ Determine extrapolation parameter $\alpha = \frac{4 T_{m-1}(\gamma_1)}{\sigma T_m(\gamma_1)} \quad \beta = \left(1 - \frac{\sigma}{2}\right)\alpha - 1 \quad \left(\gamma_1 = \frac{2}{\sigma} - 1\right)$

⑤ Perform extrapolation $x^{(l)} = \alpha x_{pow}^{(l)} + (1 - \alpha + \beta)x^{(l-1)} - \beta x^{(l-2)}$

⑥ Monitor Relative Error Reduction factor

$$\zeta_m = \frac{\|\tilde{e}^{(m)}\|}{\|\tilde{e}^{(1)}\|} \quad \xi = \frac{\zeta_m}{\zeta_{m-1}^*} = \zeta_m T_{m-1}(\gamma_1)$$

Chebyshev Acceleration Logic (3/3)

⑦ Estimate new dominance ratio (from cheby order 2)

$$\gamma_2' = \cosh\left(\frac{\cosh^{-1} \xi}{m-1}\right) \quad \text{if } \xi > 1, \left(\xi = \frac{\zeta_m}{\zeta_{m-1}^*}\right) \quad \gamma_2' = \cos\left(\frac{\cos^{-1} \xi}{m-1}\right) \quad \text{if } \xi \leq 1$$

$$\sigma' = \sigma \frac{1 + \gamma'}{2}$$

4. Reset cycle if necessary

- ① If $\zeta_m > \zeta_{m-1}^*$: Error reduction with the current σ is not effective.
- ② $m \geq m_{MAX}$
- ③ Replace $\sigma = \sigma'$
- ④ Reset $m = 0$

5. continue 3,4 until convergence

$$\frac{\|\tilde{e}^{(m)}\|}{\|x^{(l)}\|} < \varepsilon \quad \text{and } m \geq 3$$

Chebyshev for Multi Group Problem

- Group Major ordering

$$\begin{bmatrix} \begin{bmatrix} \diagdown \end{bmatrix} \\ \begin{bmatrix} \diagdown \end{bmatrix} \begin{bmatrix} \diagdown \end{bmatrix} \\ \begin{bmatrix} \diagdown \end{bmatrix} \begin{bmatrix} \diagdown \end{bmatrix} \begin{bmatrix} \diagdown \end{bmatrix} \\ \begin{bmatrix} \diagdown \end{bmatrix} \begin{bmatrix} \diagdown \end{bmatrix} \begin{bmatrix} \diagdown \end{bmatrix} \begin{bmatrix} \diagdown \end{bmatrix} \end{bmatrix} \begin{bmatrix} \phi_1 \\ \vdots \\ \phi_k \end{bmatrix} = \frac{1}{k} \begin{bmatrix} \begin{bmatrix} \diagdown \end{bmatrix} \\ \begin{bmatrix} \diagdown \end{bmatrix} \\ \begin{bmatrix} \diagdown \end{bmatrix} \\ \begin{bmatrix} \diagdown \end{bmatrix} \end{bmatrix} \begin{bmatrix} \begin{bmatrix} \diagdown \end{bmatrix} \begin{bmatrix} \diagdown \end{bmatrix} \begin{bmatrix} \diagdown \end{bmatrix} \begin{bmatrix} \diagdown \end{bmatrix} \end{bmatrix} \begin{bmatrix} \phi_1 \\ \vdots \\ \phi_k \end{bmatrix}$$

$$M \phi = \frac{1}{k} \chi v \Sigma_f \phi$$

$$M \phi = \frac{1}{k} F \phi \quad (F = \chi v \Sigma_f)$$

$$M \phi = \frac{1}{k} \chi \underbrace{v \Sigma_f}_{\psi} \cdot \phi$$

$$M \phi = \frac{1}{k} \chi \psi \rightarrow \text{Apply Chebyshev to } \psi$$

Eigenvalue Update with Fission Source

$$M \phi = \frac{1}{k} F \phi$$

Power Method with Scaling: $\phi^{(l)} = M^{-1} F \frac{\phi^{(l-1)}}{k^{(l-1)}}$

$$M^{-1} F \phi = k \phi$$

A

Inverse Power Method: $M \phi^{(l)} = F \frac{\phi^{(l-1)}}{k^{(l-1)}} = \frac{1}{k^{(l-1)}} \chi \psi^{(l-1)}$, $\chi \in R^{N,K}$, $N = G \times K$

Let $\Gamma = [I_K \cdots I_K] \in R^{K,N}$ with I_K being identity matrix of Rank K ($N = K \times G$)

$$\rightarrow \Gamma \chi = I_K \quad \because \sum_{g=1}^G \chi_g^k \equiv 1 \text{ irrespective of } k$$

$$\Gamma M \phi^{(l)} = \frac{1}{k^{(l-1)}} \psi^{(l-1)} \rightarrow K \times K \text{ linear system: Equation for entire group}$$

For large l , $M \phi^{(l)} = \frac{1}{k} \chi \psi^{(l)} \rightarrow \Gamma M \phi^{(l)} = \frac{1}{k} \psi^{(l)}$

$$\rightarrow k = \frac{\langle \psi^{(l)}, \psi^{(l)} \rangle}{\langle \psi^{(l)}, \Gamma M \phi^{(l)} \rangle} = \frac{\langle \psi^{(l)}, \psi^{(l)} \rangle}{\langle \psi^{(l)}, \frac{1}{k^{(l-1)}} \psi^{(l-1)} \rangle} = k^{(l-1)} \frac{\langle \psi^{(l)}, \psi^{(l)} \rangle}{\langle \psi^{(l)}, \psi^{(l-1)} \rangle}$$

Fission Source Iteration

1. Determine fission source at each node and fission source adjustment parameter λ

$$\psi_i = \sum_{g'=1}^G \nu \Sigma_{fg'}^i \phi_{g'}^i, \quad \lambda = \frac{1}{k}$$

Loop over groups

2. Determine source at each node for the current group

$$s_{i,g} = \lambda \chi_g \psi_i + \sum_{g'=G \min(g)}^{G \max(g)} \Sigma_{g'g}^i \phi_{g'}^i$$

3. Solve for flux for the group
4. Sweep over groups (one sweep)
5. Upscattering sweep if necessary
6. Determine new fission source
7. Estimate new k
8. Estimate pseudo error
9. Estimate dominance ratio
10. Determine extrapolation parameters
11. Do extrapolation
12. Monitor effectiveness of the current Cheby cycle