

Acceleration I: Chebychev Polynomials

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Yufan

recall the Richardson Iteration (Assume A is symmetric)

$$\begin{aligned} x^{(t)} &= x^{(t-1)} - (A x^{(t-1)} - b) \\ &= (I - A)x^{(t-1)} + b \\ &= \sum_{k=0}^t (I - A)^k b = p_t(A) \cdot b \end{aligned}$$

We want $\|p_t(A)b - x^*\| \leq \epsilon \|x^*\|$

i.e. $\|(p_t(A) \cdot A - I)x^*\| \leq \epsilon \|x^*\|$

or $\|I - A p_t(A)\|_F \leq \epsilon.$

i.e. $\|I - \lambda(A) p_t(\lambda)\| \leq \epsilon$

or $\|I - \lambda(A) p_t(\lambda(A))\| \leq \epsilon$

i.e. $\|I - \lambda p_t(\lambda)\| \leq \epsilon$ ∇ eigenvalues λ of A .

$$\|I - x p_t(x)\| \leq \epsilon \quad \nabla x \in [\lambda_{\min}, \lambda_{\max}]$$

$$q_t(x) = 1 - x p_t(x) \quad q_t(0) = 1$$

$$q_t(x) = \left(1 - \frac{x}{\lambda_{\max}(A)}\right)^t \text{ satisfies } \|q_t(x)\| \leq \left(1 - \frac{\lambda_{\min}}{\lambda_{\max}}\right)^t$$

$\sim 1 - \lambda_{\max}^{-1} \ln 1 / \text{multiplication}$

$\lambda_{\max}(A) / \lambda_{\min}(A)$

So $t = O\left(\frac{\lambda_{\max}}{\lambda_{\min}} \log \frac{1}{\epsilon}\right)$ suffices.

$$= O(K \log \frac{1}{\epsilon})$$

This is the Richardson Iteration.

Q. Can we use lower degree?

We want a polynomial $g_t(x)$ ($x \rightarrow \infty \Rightarrow g_t(x) \rightarrow \infty$) with $|g_t(x)|$ as small as possible for $x \in [-1, 1]$ (say, after normalizing $[\lambda_{\min}, \lambda_{\max}] \rightarrow [-1, 1]$).

Ans. Chebyshev polynomials!

$$\begin{aligned} t^{\text{th}} \text{ C.P.} &\rightarrow T_t(\cos \theta) = \cos(t\theta) \\ \text{is the degree} \\ t \text{ poly of } t. & (T_t(x) = \cos(t \cos^{-1}(x)) \text{ for } x \in [-1, 1]) \end{aligned}$$

$$\cos(\theta + \alpha) = \cos \theta \cos \alpha - \sin \theta \sin \alpha$$

$$\therefore \cos(t\theta) = \cos((t-1)\theta) \cos \theta - \sin((t-1)\theta) \sin \theta$$

$$\cos((t-2)\theta) = \cos((t-1)\theta) \cos \theta + \sin((t-1)\theta) \sin \theta$$

$$\Rightarrow \cos(t\theta) = 2 \cos((t-1)\theta) \cos \theta - \cos((t-2)\theta)$$

$$T_t(x) = 2x T_{t-1}(x) - T_{t-2}(x) \quad (*)$$

$$T_1(x) = 1 \quad T_2(x) = x \quad T_3(x) = 2x^2 - 1 \dots$$

$$T_0(x) = 1, \quad T_1(x) = x, \quad T_2(x) = 2x^2 - 1$$

Note that $T_t(\cosh \theta) = \cosh(t \coth^{-1}(\theta))$ also holds

$$\text{since } \cosh \theta = \frac{e^\theta + e^{-\theta}}{2} \quad \sinh \theta = \frac{e^\theta - e^{-\theta}}{2}$$

satisfies $\cosh(\theta + \alpha) = \cosh(\theta)\cosh(\alpha) + \sinh(\theta)\sinh(\alpha)$

so we get (*) again.

$$\text{For } x \geq 1, \quad T_t(x) = \cosh(t \coth^{-1}(x)).$$

$$x \leq -1 \quad T_t(x) = (-1)^t \cosh(t \coth^{-1}(-x))$$

$$\underline{\text{Lemma.}} \quad T_t(1+\gamma) \geq \frac{1}{2} (1 + \sqrt{2\gamma})^t \quad \gamma > 0.$$

$$\underline{\text{Pf.}} \quad T_t(x) = \frac{1}{2} (e^{t \coth^{-1}(x)} + e^{-t \coth^{-1}(x)})$$

$$\coth^{-1}(x) = \ln(x + \sqrt{x^2 - 1}) \text{ for } x \geq 1.$$

$$\begin{aligned} &\geq \frac{1}{2} (x + \sqrt{x^2 - 1})^t \\ &= \frac{1}{2} (1 + \gamma + \sqrt{2\gamma + \gamma^2})^t \geq \frac{1}{2} (1 + \sqrt{2\gamma})^t. \end{aligned}$$

$$\text{1. } \therefore \text{1. hence } t = O(\sqrt{k} \log \frac{1}{\epsilon}).$$

Thm. $\exists q$ of degree $t = O(\sqrt{K} \log \frac{1}{\varepsilon})$.

Pf. shift: $f(x) = \frac{\lambda_{\max} + \lambda_{\min} - 2x}{\lambda_{\max} - \lambda_{\min}}$

$$f(x) = \begin{cases} -1 & x = \lambda_{\max} \\ 1 & x = \lambda_{\min} \\ \frac{\lambda_{\max} + \lambda_{\min}}{\lambda_{\max} - \lambda_{\min}} & x = 0 \end{cases}$$

$$q(f(x)) = \frac{T_t(f(x))}{T_t(f(0))} \quad \text{s.t. } q(0) = 1.$$

$\forall x: f(x) \in [-1, 1] \quad |T_t(f(x))| \leq 1. \quad (\cos \theta)$.

$$\begin{aligned} T_t(f(0)) &= T_t\left(1 + \frac{2}{\frac{\lambda_{\max} - 1}{\lambda_{\min}}}\right) = T_t\left(1 + \frac{2}{K-1}\right) \\ &\geq \frac{1}{2} \left(1 + \sqrt{\frac{2}{K-1}}\right)^t \end{aligned}$$

$$\therefore |q(x)| \leq \frac{2}{\left(1 + \sqrt{\frac{2}{K-1}}\right)^t} \quad \forall x \in [-1, 1]$$

i.e. $t = O(\sqrt{K-1} \cdot \log \frac{1}{\varepsilon})$ suffices.

Another, more general proof.

$\sim \dots \sim \sim \dots \sim$ degree d s.t. \sim^2 .

Thm. $\forall s, d \exists p(x)$ of degree d s.t. $\max_{x \in [-1, 1]} |p(x) - x^s| \leq 2e^{-d^2/2s}$

Cor. $(1 - \frac{x}{x_{\max}})^s$ can be approximated to within ϵ by $p(x)$ of degree $\sqrt{s \log \frac{1}{\epsilon}}$

Since we use $s = O(k \log \frac{1}{\epsilon})$

$p(x)$ of degree $O(\sqrt{k} \log \frac{1}{\epsilon})$ suffices.

Pf. (of Thm). Let $Y_s = \sum_{i=1}^s Y_i \quad Y_i \sim \{-1, 1\}$ uniform.

$$T_a(x) = T_{|a|}(x)$$

$$\mathbb{E} T_{z_s} = \frac{1}{2} (\mathbb{E} T_{z_{s+1}} + \mathbb{E} T_{z_{s-1}})$$

$$\text{But we know } x T_z(x) = \frac{1}{2} (T_{z+1}(x) + \frac{1}{2} T_{z-1}(x))$$

$$\Rightarrow \mathbb{E} T_{z_s} = x \mathbb{E} T_{z_{s-1}}(x) = x^s.$$

$$\text{Let } p(x) = \mathbb{E} T_{z_s}(x) \cdot \mathbf{1}_{|z_s| \leq d}$$

$$\text{Then } \max |p(x) - x^s| = \max |\mathbb{E} T_{z_s}(x) \cdot \mathbf{1}_{|z_s| \leq d}|$$

$$\begin{aligned}
 \text{Then } \max_{x \in [-1, 1]} |p(x) - x^*| &= \max_{x \in [-1, 1]} \left| E_{z_s} [T_{z_s}(x) \cdot \mathbb{1}_{|z_s| > d}] \right| \\
 &= \max_{x \in [-1, 1]} |E_{z_s} [T_{z_s}(x)]| \cdot \mathbb{1}_{|z_s| > d} \\
 &\leq P_\lambda(|z_s| > d) \\
 &\leq 2e^{-\frac{d^2}{2s}}.
 \end{aligned}$$
