

Preconditioning

Next Lecture: time $\tilde{O}(m \ln \frac{1}{\epsilon})$
today $\tilde{O}(m^{1/3} \ln \frac{1}{\epsilon})$

Solve equations in A by solving systems in a "preconditioner" B , and multiplying by A .

CG, Richardson, Chebyshev just used multiplies by A .

of iterations depends on $\kappa(A, B) = \frac{\lambda_{\max}(B^T A)}{\lambda_{\min}(B^T A)}$,

orthogonal to common nullspace, if there is one.

lem $\lambda_{\max}(B^T A) = \min \{ \beta : A \preceq \beta B \}$

$$\lambda_{\min}(B^T A) = \max \{ \alpha : \alpha B \preceq A \}$$

proof $A \preceq \beta B$ iff $\forall x \quad x^T A x \leq \beta x^T B x$

$$\Leftrightarrow \frac{x^T A x}{x^T B x} \leq \beta$$

$$\Leftrightarrow \frac{y^T B^{-1/2} A B^{-1/2} y}{y^T y} \leq \beta$$

$$\Leftrightarrow \lambda_{\max}(B^{-1/2} A B^{-1/2}) = \lambda_{\max}(B^T A) \leq \beta$$

So, $\kappa(A, B) \leq \beta/\alpha$ where $\alpha B \preceq A \preceq \beta B$

Cor. $A \preceq B$ iff $B^T \preceq A^{-1}$

Recall, $\tilde{x}$ is ε -approx sol to $Ax=b$ if
$$\|\tilde{x} - x\|_A \leq \varepsilon \|A\|.$$

A very good precondition would be B st. $(1-\varepsilon)B \leq A \leq (1+\varepsilon)B$
By con, and a result from last lecture,

$$\|B^{-1}Ax - x\|_A \leq \varepsilon \|A\| \text{ for all } x.$$

Iterative Refinement is a procedure for increasing accuracy.

$$\text{Set } x_1 = B^{-1}b = B^{-1}Ax$$

$$\text{residual } r_1 = b - Ax_1$$

$$\text{If } Ay = r_1, \text{ then } A(x_1 + y) = Ax_1 + b - Ax_1 = b$$

$$\text{So, set } x_2 = B^{-1}r_1$$

$$\begin{aligned} \text{Now, } \|x - (x_1 + x_2)\|_A &= \|(x - x_1) - x_2\|_A \\ &\leq \varepsilon \|(x - x_1)\|_A \\ &\leq \varepsilon^2 \|x\|_A \end{aligned}$$

If repeat k times, can get an ε^k approx solution
after k iterations
each using a mult by A
solve in B

So, once can get an ε -approx for some constant ε
can achieve $\ln 1/\varepsilon$ dependence

Origin: going from low to high precision.

Most preconditioners are not that good.

But, if can solve B quickly, then apply in CG or Chebyshev.

Let $\lambda_1 \dots \lambda_n$ be eigs of $B^T A =$ eigs of $A^{1/2} B^{-1} A^{1/2}$

If $q(t) = 1 - x p(x)$ is a poly s.t. $|q(\lambda_i)| \leq \varepsilon \quad \forall i$,

then $\tilde{x} \triangleq p(B^T A) B^T b$

is an ε -approx solution to $Ax = b$

proof:

$$\begin{aligned} \|x - \tilde{x}\|_A &= \|A^{1/2} x - A^{1/2} \tilde{x}\| \\ &= \|A^{1/2} x - A^{1/2} p_t(B^T A) B^T A x\| \\ &= \|A^{1/2} x - A^{1/2} p_t(B^T A) B^T A^{1/2} \cdot A^{1/2} x\| \\ &\leq \|I - A^{1/2} p_t(B^T A) B^T A^{1/2}\| \cdot \|x\|_A \end{aligned}$$

$$\begin{aligned} I - A^{1/2} p_t(B^T A) B^T A^{1/2} &= I - p_t(A^{1/2} B^{-1} A^{1/2}) A^{1/2} B^{-1} A^{1/2} \\ &= q_t(A^{1/2} B^{-1} A^{1/2}) \end{aligned}$$

As $A^{1/2} B^{-1} A^{1/2}$ is symmetric,

$$\|q(A^{1/2} B^{-1} A^{1/2})\| \leq \varepsilon$$

Preconditioned CG - PCG finds the best polynomial.

But, because polynomial depends on input, is not a linear operator.

Precon Chebyshev - needs to know α and β , but is a linear operator.

Laplacians

Udya: precondition $L_G \succeq L_H$ for $H \subseteq G$

Guarantee $L_H \preceq L_G$

Just need to know β st. $L_G \preceq \beta L_H$

Use a spanning tree T .

Can solve equations in L_T in time $O(n)$ -

elimination takes time $O(n)$ because
every tree has a vertex of degree 1,
and eliminating it gives another tree.

Will show is a tree T st. $\beta \leq C \cdot m \cdot \lg n \cdot \lg \lg n$,
for some constant C .

$$\text{Now } \lambda_{\max}(L_H^\dagger L_G) \leq \text{Tr}[L_H^\dagger L_G]$$

$$\text{lem. } \text{Tr}[L_H^\dagger L_G] = \sum_{(a,b) \in E} w_{a,b} \text{Stretch}_T(a,b)$$

where view length of an edge as $\frac{1}{\text{weight}}$

$\text{stretch}_T(a,b) = \text{length of path in } T \text{ from } a \text{ to } b$

mult by $w_{a,b} = \text{divide by length of } (a,b) \text{ edge}$

proof

$$\text{Write } L_G = \sum_{a \sim b} w_{a,b} (\delta_a - \delta_b)(\delta_a - \delta_b)^T$$

$$\text{Tr}[L_H^+ L_G] = \sum_{a \sim b} w_{a,b} \text{Tr}[L_H^+ (\delta_a - \delta_b)(\delta_a - \delta_b)^T]$$

$$= \sum_{a \sim b} w_{a,b} (\delta_a - \delta_b)^T L_H^+ (\delta_a - \delta_b)$$

$$= \sum_{a \sim b} w_{a,b} \text{Reff}_T(a,b)$$

$$\text{Reff}_T(a,b) = \sum \frac{1}{w_i} \quad \text{sum over weights of edges}$$

on the unique path in T between a and b .

$$= \sum_{a \sim b} w_{a,b} \text{Stretch}_T(a,b)$$

Theorem Every weighted graph $G=(V,E,w)$

has a spanning Tree $T=(V,F,w)$ with $F \subseteq E$

$$\text{s.t. } \sum_{(a,b) \in E} w_{a,b} \text{Stretch}_T(a,b) \leq O(m \lg n \lg \lg n)$$

And, can compute it in time $O(m \lg n \lg \lg n)$

$\searrow$ $= \text{Stretch}_T(G)$

Given T , can compute $\text{stretch}_T(G)$, use it to set β ,
and run Power Cheby for $\leq O(\sqrt{\beta} \lg^{1/2})$ iterations
to get ε -accurate solution.

Each iteration takes time $O(m)$ - mult by L_G
 $O(n)$ - solve in L_H

$$\text{so total is } O(m^{3/2} \sqrt{\lg n \lg \lg n} \lg^{1/2})$$

Using PCG can do better, as there is a better polynomial.
Reason: there can be at most k eigenvalues $> \text{Tr}(L_H^\dagger L_G)/k$

lem let $1 \leq \lambda_1 \leq \dots \leq \lambda_n$

and $\lambda_{n-k} \leq \beta$.

Then for every $t \geq k$, $\exists$ poly $q(x)$ of degree t s.t.

$$q(0) = 1 \text{ and } |q(\lambda_i)| \leq 2 \exp(-2(t-k)/\sqrt{\beta})$$

use with $\beta = \text{Tr}(L_H^\dagger L_G)^{2/3}$, $k = \text{Tr}(L_H^\dagger L_G)^{1/3}$,
 $t = (k+1) \ln(1/\varepsilon)$ to get ε -accurate solution

proof let $r(x)$ be poly of degree $t-k$ s.t.

$$r(0) = 1, |r(x)| \leq 2 \exp(-2(t-k)/\sqrt{\beta}) \quad \forall \quad 1 \leq x \leq \beta$$

constructed last week.

$$\text{Set } q(x) = \tau(x) \prod_{j=n-k+1}^n \left(1 - \frac{x}{\lambda_j}\right)$$

$$\text{so } q(0) = \tau(0) = 1$$

$$q(\lambda_i) = 0 \quad i > n-k$$

$$\text{for } i \leq n-k, \quad \lambda_i \leq \beta$$

$$\text{so } q(\lambda_i) = \underbrace{\tau(\lambda_i)}_{\leq \varepsilon} \underbrace{\prod_{j=n-k+1}^n \left(1 - \frac{\lambda_i}{\lambda_j}\right)}_{\in (0,1)}$$

$$|q(\lambda_i)| \leq \varepsilon$$